Intermittent Participation, Wages and the Labour Market

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Abstract

This thesis is centered on the labour market fortunes of women with intermittent participation. We examine whether there are earnings losses associated with time out of work, the role of disjoint employment histories in the explanation of the gender wage gap, and the duration structure of intermittent participation.

The first Chapter presents an introduction to the issues. Chapter 2 documents the main labour market events that concern women over the last twenty-five years in order to motivate the empirical work. Chapter 3 gives details of the principal data sets used, whilst Chapter 4 surveys the main theoretical developments of female labour supply and earnings determination.

Chapter 5 analyses the effect of work interruptions on earnings. We show that use of potential experience in wage equations may seriously overestimate the returns to work experience. The average wage gain to actual work experience is between 1 to 2 per cent a year and is confined to women with full-time work experience. Time spent out of work has a negative effect on re-entry wages. The average earnings loss is around 2 per cent a year. The magnitude of the earnings penalty varies with the type of out of work spell. Those who are unemployed suffer the highest earnings penalty. These results hold in the presence of controls for unobserved heterogeneity.

Chapter 6 presents a new decomposition of the gender pay gap using panel information on employment transitions and wages. On initial entry into the labour market, the earnings of men and women are very similar. As earnings growth while in continuous employment shows no significant gender differences, male and female earnings will follow each other. Differences start to emerge once there are breaks in work. On re-entry to the labour market, both men and women obtain lower wages than before, but men return at higher wages than women: with the re-entry gender pay gap rising with age. This, combined with the fact that women are more likely to have breaks, is the explanation of why women's pay increasingly falls behind the pay of men over the life cycle.

Chapter 7 models the duration of time spent in childcare in detail. We show that the relative propensity to return to part-time work rises with the age of the mother. Women who take childcare breaks relatively early in their careers spend less time out of work and are more likely to re-enter to full-time work. The age and number of children appear to be the most important factors behind this observation. Women are more likely to return to full-time work the fewer the number of children they have and the older the children are. There seems to be little evidence that women in the age range analysed use part-time work as a stepping stone to full-time work.

Chapter 8 concludes by considering the implications of these results.

Acknowledgements

I would like to thank my supervisors for their comments, without whose help several aspects of this research would have suffered. I would also like to acknowledge my colleagues, friends and family who have given me continuous support. In particular, I would like to thank Lorraine Dearden for sharing her experiences of the pitfalls of some of the data sets used in this work.

Author's Declaration

I declare that the work in this thesis was carried out in accordance with the Regulations of the University of Bristol. The work is original except where indicated by special reference in the text and no part of the dissertation has been submitted for any other degree. The work is, with the exception of Chapter Six, wholly my own. Chapter Six was written in collaboration with Professor Alan Manning, London School of Economics.

Any views expressed in this thesis are those of the author and in no way represent those of the University of Bristol.

The dissertation has not been presented to any other University for examination either in the United Kingdom or overseas.

Signed: J Robinson Date: 5/08

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Chapter 1

Introduction

1.1 Motivation

In 1999, the European Union issued a set of guidelines aimed at tackling the gender gaps in employment and earnings and to improve policies to reconcile work and family life. Equality of opportunity across genders is a fundamental starting point put firmly on the European agenda at the Luxembourg Jobs Summit in November 1997.[1] How far are such movements based on brave rhetoric, and to what extent is there economic evidence that the alignment of child-rearing and working life is a harmonious one? This thesis provides a detailed assessment of these issues and presents fresh insight into some of the forces at play. Essentially, it is concerned with three issues. First, it investigates the economic fortunes of those women with intermittent labour force participation, specifically the effect of time out of work on earnings. Second, it examines the duration structure of intermittent participation, and, third, it explains the role of disjoint employment histories in the explanation of the gender wage gap.

Female labour force participation has been rising in most of the Western world since the late nineteenth century. To attribute all of this increase in supply as a response to higher female real wages overlooks the huge changes in policies and attitudes that have taken place. Most recently, the provision of equal pay acts and maternity leave legislation have had a significant impact on the capacity of women to balance market and domestic work. The European Union's guidelines explicitly recognise that a large contribution to this objective can be made through policy. The pattern of female labour force participation has changed dramatically over the post-war period. In the UK, more women in the 25-45 age group are to be found economically active than ever before. However, significant numbers of women still experience discontinuities in their employment history at the time of childbirth and various models exist which attempt to account for this observable feature.

[1] See Employment and Social Affairs Unit (1999).

During this time period, real wages have increased (see Juhn and Murphy (1996), for example). This has made the opportunity to stay at home throughout the childbearing period an affordable option for large numbers of women, thereby reducing female labour supply. However, this negative effect on supply has been moderated through an increase in the opportunity costs of female nonparticipation. Additionally, an increase in real female wages has made the purchase of quality childcare affordable for some women. Given an expansion in post-war female job possibilities, the proportion of female entrants to the labour market has also risen.

An increase in job opportunities has occurred alongside an increase in educational possibilities for women and these have been subsequently rewarded in the market. Medical advances have led to far greater female control over fertility. Technological progress has seen the advent of a huge array of labour saving devices in the average household. These factors, too, have led to increases in the labour supply of women.

The theoretical underpinnings throughout this thesis lie within the framework of the theory of human capital. According to the basic theory, workers continue to invest in human capital up until the point where the internal rate of return on such acquisitions equals the market rate of interest. The underlying implication of this is that engaging in extra years of education, say, is somehow recognised in a higher future income stream once post-compulsory education is complete. Greater amounts of education feed into higher worker productivity and justify the payment of additional earnings such that the wage is equal to the marginal revenue product in a perfectly competitive market. Rates of return to schooling vary depending upon the level of education and gender. It can be shown that intermittent workers (who are usually female) receive lower returns to human capital than continuous workers and an explanation of this phenomenon is required. If it is understood that intermittent workers somehow lose the effects of education and training during periods spent outside the labour force, then their pre-interruption acquisition of such human capital needs to be justified another way. Failing this, the acquisition represents a waste of scarce societal resources and misspent time.

Gronau (1988) maintains that intermittent workers alter their behaviour as a result of the lower returns which they perceive due to their discontinuous work patterns. Such workers are less likely to enter and remain in the labour force due to their prediction of low lifetime earnings as a result of intermittent supply. It is obviously a difficult task to ascertain what level of wages this group would earn if they had not taken time away from employment and this area is fraught with the self-selectivity problems highlighted by Heckman (1979). It can be argued that workers are less likely to engage in human capital investment during an interruption and as such withdrawal indicates lost productive potential. The empirical section of this research deals with these issues more fully.

The problems of misallocation of labour into various areas of employment are further compounded in today's economic climate. The move to more flexible working patterns, especially in the tertiary sector, has been effective in reducing both the duration and the frequency of periods spent outside the labour force (Employment Gazette (1994)). However, a penalty in terms of lower post-interruption earnings still exists. If workers continue to assume that reduced post-interruption earnings prevail then this imperfect information will result in economic inefficiency. For these reasons, it is important to estimate the size of the reduced post-interruption wage for economies such as that of the United Kingdom.

1.2 Scope of the Analysis

In order to deal with the issues set out above, the structure of this thesis is as follows. In the following chapter, an overview of the British labour market in the last 25 years is given. In particular, we analyse the labour market participation and earnings patterns of men and different groups of women. These trends provide the justification for further empirical analysis of the issues involving intermittent workers.

This thesis is largely an empirical work. The issues it examines cannot be dealt with through the use of one sole data set. Chapter 3, therefore, provides a survey of the different

data sets used. We also give a detailed and in-depth account of the problems experienced with the data, our data cleaning procedures, and the construction of key variables.

The introductory section of Chapter 4 sets out the existing knowledge of labour supply and human capital theory on which this thesis is predicated. The latter half of the Chapter looks in detail at two human capital models of intermittent participation developed in the US and in the Netherlands. These models, explaining how and why earnings may be affected by time spent out of employment, form the basis of the empirical work in Chapter 5. Here, we use regression analysis to analyse the determinants of earnings and to estimate wage equations for female workers who experience absence from the labour market. The analysis, using the National Child Development Study, produces two key findings. First, it establishes that there is a wage penalty associated with taking a break from continuous employment. Second, the wage penalty is seen to vary with the nature of the break. With respect to the determinants of female participation in spells of domestic activity, we single out the effects of education and family characteristics. It transpires that, even allowing for selectivity effects that may be associated with differing tastes for work, female workers who have time away from the labour market still experience a negative impact upon their re-entry wages.

Most studies of the gender pay gap use cross-section earnings functions to apply a Oaxaca decomposition to the contributions of differences in characteristics and coefficients. However, the accounts that these studies provide of the gender pay gap are often hard to relate to the more informal stories told about the sources of women's disadvantage in the labour market. In Chapter 6, a panel data set is used to decompose average earnings into the contribution of the average starting wage for workers entering paid work from non-employment, average wage growth for those in continuous employment and the fraction of workers entering employment. This decomposition is used to identify, first, the source of the pay gap between men and women, and, second, the gap between women in full- and part-time work using data drawn from the British Household Panel Survey. Comparing men and women, we find no significant differences in wage growth on the job

so that the source of the gender pay gap comes from the entrant pay gap and the share of entrants. Looking at long-run changes suggests that we would expect to see a further narrowing of the pay gap in the future.

Given all the above processes at work, much interest has been generated in the modelling of female labour supply, both in the static and dynamic framework. In general, the longer the time out of work, the heavier the wage penalty. Chapter 7 focuses on the principle features of the duration of time out and the nature of the subsequent re-entry, in order to establish the principle factors determining the length of time out. Using duration analysis, the Chapter shows that the relative propensity to return to part-time work rises with the age of the mother. Women who end childcare breaks relatively early in their careers spend less time out of work and are more likely to re-enter to full-time work. The age and number of children appear to be the most important factors behind this observation. Women are more likely to return to full-time work, the fewer the number of children they have and the older the children are.

Chapter 8 concludes by giving an overview of the main findings of the thesis, scope for future work and possible policy implications.

Chapter 2

Recent Developments in the Female Labour Market in Britain

2.1 Introduction

This thesis is primarily concerned with the economic fortunes of women. We begin, therefore, with an overview of the key events regarding women that have shaped the labour market over the last two decades. One of the most notable features has been the advancement of women at the workplace relative to men. The improved prospects of women are apparent in both employment and earnings. Economists, demographers and labour market policy-makers have all cited reasons for the recent developments, with varying degrees of emphasis on fertility, labour supply and demand. (summarised in Ferber (1998)). Declining fertility rates, marital dissolution, changing attitudes toward women in the workplace, improvements in household labour-saving technology and the facilitation of the involvement of women in the world of work through maternity leave and the state provision of in-work benefits (such as Family Credit and its replacement the Working Families Tax Credit), have all contributed to the increase in female labour market participation (see amongst others Joshi and Owen (1985), and Joshi and Paci (1999)). However, casual observation would suggest that, whilst female labour market participation has increased, this has not been of the same order across all groups of women with different family status. For example, there has traditionally been a strong negative correlation between the presence of young children in the household and female labour supply (see Nakamura and Nakamura (1981)). The impact of children also affects the participation of women across the life cycle.

Similar progress in women's wages may be observed over the same time period. Increased educational attainment and work experience (partly influenced by the same factors which facilitated increased participation) are cited as reasons for the narrowing of the gender pay gap, (Harkness (1996)). Here again, we may expect these influences to vary across groups of women and to affect the pay gap in varying degrees. For example, differences in educational attainment or on-the-job training may mean that pay for older women may lag behind, if younger cohorts are more educated or receive more training. Further, whether women work full- or part-time may also influence earnings, if

there are pay penalties to working part-time. Differences in part-time working across age groups will then affect the life-cycle earnings profile. Moreover, since the majority of part-time workers are women, any part-time pay penalty will influence the gender pay gap.

This Chapter uses General Household Survey (GHS) data to summarise the changes in the economic performance of women (as measured by earnings and employment), relative to men since 1975. The GHS is the only British data set that provides continuous information on employment and earnings for this period. We also focus our discussion on the years covered by the other data sets used in this thesis.[1] Thus, the data incorporate the time span from when our sample of women in Chapter 5 have passed compulsory school-leaving age (1975), to the end year for our panel of women in Chapter 6 (1995). Throughout this time window, both the Sex Discrimination and the Equal Pay Acts were in place, which may have had a bearing on events. The Equal Pay Act of 1970 made the process of offering different wages to men and women illegal. This was later extended in 1983 to cover equal pay to work of equal value. The Sex Discrimination Act implemented in 1975 prohibited gender discrimination in hiring. The subsequent Employment Protection Act, introduced in 1979, established the right to have maternity leave. The GHS data cannot allow us to observe earnings or employment before these Acts. This Chapter therefore goes on to assess the labour market performance of different groups of women in the light of these events.

2.2 Economic Activity Rates

Historically, women in Britain have had lower unemployment rates than men. This is in part because women have tended to withdraw from the labour force when not in work in much greater numbers than men do. The means-tested component of the unemployment benefit system offers no incentive for many women to register as unemployed, if a partner, if present, is in full-time work. This thesis relies on household survey data. It may be, however, that the information contained in survey data will also suffer from a similar distortion if there is a correlation between registering to receive unemployment benefit and satisfying the active job search criteria in a survey. A more complete guide

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[1] 1991, for example, is a relevant year for the NCDS data set.

to relative economic performance is therefore to divide the labour market into three states (employment, unemployment and inactivity), and then to look at differences in employment and participation rates by gender.

Table 2.1 and Figure 2.1 confirm that more women than ever are now in work. The employment rate for women rose from 0.61 in 1975 to 0.67 in 1995. By contrast, the employment rate for men has fallen by around 14 percentage points over the same period, from 0.90 in 1975 to 0.76 in 1995. As a result of rising employment amongst women and falling employment amongst men, the gender employment-rate gap narrowed from 0.29 to 0.10 over the period. These two opposing trends are not yet equal and opposite in magnitude. The total employment rate was still 4.5 percentage points lower in 1995 than in 1975. Moreover, Figure 2.1 shows that female employment rates rose most during the economic boom of the late 1980's. Male employment rates fell most in the recessions of the early 1980's and early 1990's. By contrast, female employment rates were hardly affected during the last recession. These cyclical movements suggest that the gender employment gap may well be equalised during the next economic downturn.

The information on employment rates in Table 2.1 tells us little of the variety of experience between members of the gender groups. Table 2.2 and Figure 2.2 give employment rates conditional on age from the beginning to the end of the sample period. The figures portray three-year averages, in order to boost the sample sizes within each age group. One of the notable features of Figure 2.2 is the fall in employment for women in their mid-twenties to early thirties. Hitherto, women seemed to stop working in their childbearing years: this is now less prevalent. Figure 2.2 shows that in 1975, female employment rates exhibited the characteristic double-peak pattern. By 1995, this shape was no longer so clearly discernible. Indeed, the pattern in this year is very similar to that of male rates. Male employment rates have fallen at every age: more so for those under 24 and those over 50 years of age. This reflects rises in the staying-on rates for higher education and the movement into inactivity of men over 50. Again, the trends for men and women act to narrow the employment gaps by age. By 1991, young male 16 year-olds enjoyed similar economic activity patterns to females of the same age, (compare the 49 per cent rate for females with the 46 per cent rate for

males in Table 2.2). However, females aged 25 in 1991 still had lower economic activity rates than males (62 per cent for females compared to 81 per cent for males). The employment gap had narrowed most by 1991 for male and females over fifty, (compare the 73 per cent rate for females and the 82 per cent rate for males in 1991 with the rates of 68 per cent and 94 per cent in 1975). These trends have continued into the mid-1990s. In passing, we note that Figure 2.2 suggests a move of women as a group to postpone the birth and rearing of children (the dip in age-specific employment rate moves to the right) or the fact that the frequency and length of time out is becoming smaller (the dip becomes shallower). Whilst the graph of the employment rate is smoother than before, the drop in rate now occurs at a higher age. Despite clear health disincentives,[2] the trend seems to be in this direction. The traditional pattern of discontinuous economic activity throughout their early twenties until mid-thirties is in stark contrast to patterns observed in mainland Europe (in countries such as France, say). It would seem that French women fall into two separate groups: those who work continuously without career breaks and those who are permanently out of the labour force (Dex, Walters and Alden (1994)). However, the enforcement of comparatively recent European maternity rights[3] has meant that increasing numbers of British women are now able to retain a foothold in the labour market through their childbearing years. A sizable proportion of these women return to, and then remain with, their pre-break employer. The data above cannot however confirm whether the women return to the same employer. Since the employment rate is a product of the inflow rate and the average duration of employment, the evidence of higher employment rates (in the age range 26 to 35 years) can arise from any of the following. A rise in the average duration, or a rise in the inflow rate, or a combination of both these factors. The inflow rate may reflect child-rearing experiences for this age range that in turn may indicate both fertility rates and the speed of return to work. For a given inflow rate, the higher employment rates suggest a longer duration at work, consistent with shorter breaks (or no breaks at all).

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[2] For example, the well-publicised association between some forms of cancer and the delay of the birth of a first-born child to after the age of thirty.

[3] The 1993 amendments brought down the qualification period of maternity leave to 1 year from 2 years for full-time workers and to 1 year from 5 years for part-time workers.

Historically, during childbearing years, women were likely to be found in the out-of-the-labour force state. Table 2.3 and Figure 2.3 show how employment rates across the genders vary with the age of the youngest child present in the household.[4] Figure 2.3 demonstrates how the absence of young children in the household leads to a pattern of female employment rates which most closely mimics the total employment rate of men. We witness that for women with no children, the employment rate over the fifteen year period has remained relatively constant. Employment rates for women with children are lower than for women with no dependent children. One explanation of the constraining force of the presence of young children on female labour supply is that young children have high costs in terms of time and thereby raise the reservation wage of being in work (Becker (1964)). As the age of the youngest child rises, the decision to participate and thereby the employment rates of women are affected less and less. This is what we observe from the data. Female employment rates rise with the age of the youngest child. Figure 2.3 also shows how the employment rate has risen most amongst women with very young children in the last decade. Women with young children are currently in employment in greater numbers than ever before. In 1995, 41 per cent of women with a child under one were in work, in contrast to just 17 per cent in 1981, (see Table 2.3). Note that there is no association between employment rates and the age of youngest child for men.

2.3 Earnings

Whilst the differences in employment rates between men and women are easily visible, what can be said about the differences in earnings? In 1995, the typical woman could expect to be paid an average of £ 6.63 an hour. However, a man could expect to earn £8.98 an hour, (in January 1998 prices), so that, in 1995, women earned, on average, some 73 per cent of the average male hourly wage. That the gender pay gap had started to narrow over time since the early 1970's (particularly after the implementation of the Equal Pay Act) is well documented, (see Joshi and Paci (1998)). Table 2.4 shows that the female earnings relative to male rose by 10 points from .64 to .74 between 1975 and 1995. Of course, wages differ considerably with full- and part-time work status, as Table 2.4 and Figure 2.6 indicates. The average full-time job pays around 20 per cent

[4] Information on the age of youngest child is only available from 1980.

more than the average part-time job. This may be because part-time workers receive lower returns to human capital characteristics, such as education and work experience, than their full-time counterparts (Harkness (1996)), or because they have less human capital. This issue is further explored in Chapters 5 and 6. Note that the gap[5] between female full-time wages and male wages has narrowed more than the gap between female part-time and male wages (Figure 2.7 and Table 2.4). In 1975, a woman in full-time work could expect to earn around 63 per cent of the average male wage. By 1995, a woman in part-time work could earn around 66 per cent of the average male wage, whilst full-timers were earning 80 per cent of the average male wage. Why might part-time jobs now carry a wage penalty whereas up until the mid-1970s they proffered a wage premium? One possible explanation is outlined in Table 2.5 and Figure 2.8 which show that the distribution of part-time work has moved sharply toward younger workers and those over fifty. It may be that the low relative hourly wage for part-time work in the 1990's results because part-time work consists more of younger workers (who have little in the way of work experience) than in the past (compare 37 per cent of sixteen year-olds in part-time work in 1975 with 82 per cent in 1995). Figure 2.9 confirms that the share of part-time work accounted for by younger female workers is rising over time. Around 8 per cent of part-time jobs are now accounted for by teenagers compared with around 4 per cent twenty years ago.

Given this pattern of participation in the UK, what can be said about the financial cost of taking a break in employment? What impact is there on stocks of human capital when a worker experiences an interruption? The GHS provides no information on actual work experience, but an initial insight may be obtained by examining the wage gained by women conditional on the age of the youngest child. Table 2.6 illustrates wages by age of youngest child. In 1995, a woman with a youngest child aged less than one in part-time work was earning £7.50 an hour, some £2.25 more than a woman locked into part-time work by the time her youngest child was aged six. It is notable that in the early part of our time window, childless women in part-time work suffered a wage penalty in contrast to part-time working mothers with young child(ren). However, this effect lessened over the period: as part-time work moved into the domain of young female workers. Table 2.7 provides two snapshots of the distribution of female part-

[5] The gap used here means the ratio of female to male earnings.

time work by age of youngest child in the household. In the early period of our sample, 1980-82, the share of women in part-time work is some .09 percentage points higher on average across women with youngest child over six than in the 1993-95 period. However, amongst childless women, the occurrence of part-time work was slightly higher in the later period. It would seem that whereas once, part-time work was associated with women with young children, it has lately been chosen as a long-term option for women without children.

2.4 Summary

The evidence presented in this overview of the labour market events in Britain over the last two decades suggest that women have experienced improvements in workplace fortunes, as measured by rising employment rates and wages. More women are in work than ever before and their wages have improved both in real terms and relative to men. Women also seem to be returning to work after childbirth much sooner than before, as evidenced by the rise in employment rates in the principle childbearing ages. However, it is clear that not all women have benefited equally from these changes. It seems that women in part-time work have not enjoyed relative wage gains to the same extent as their full-time counterparts and that the part-time work has shifted toward younger women.

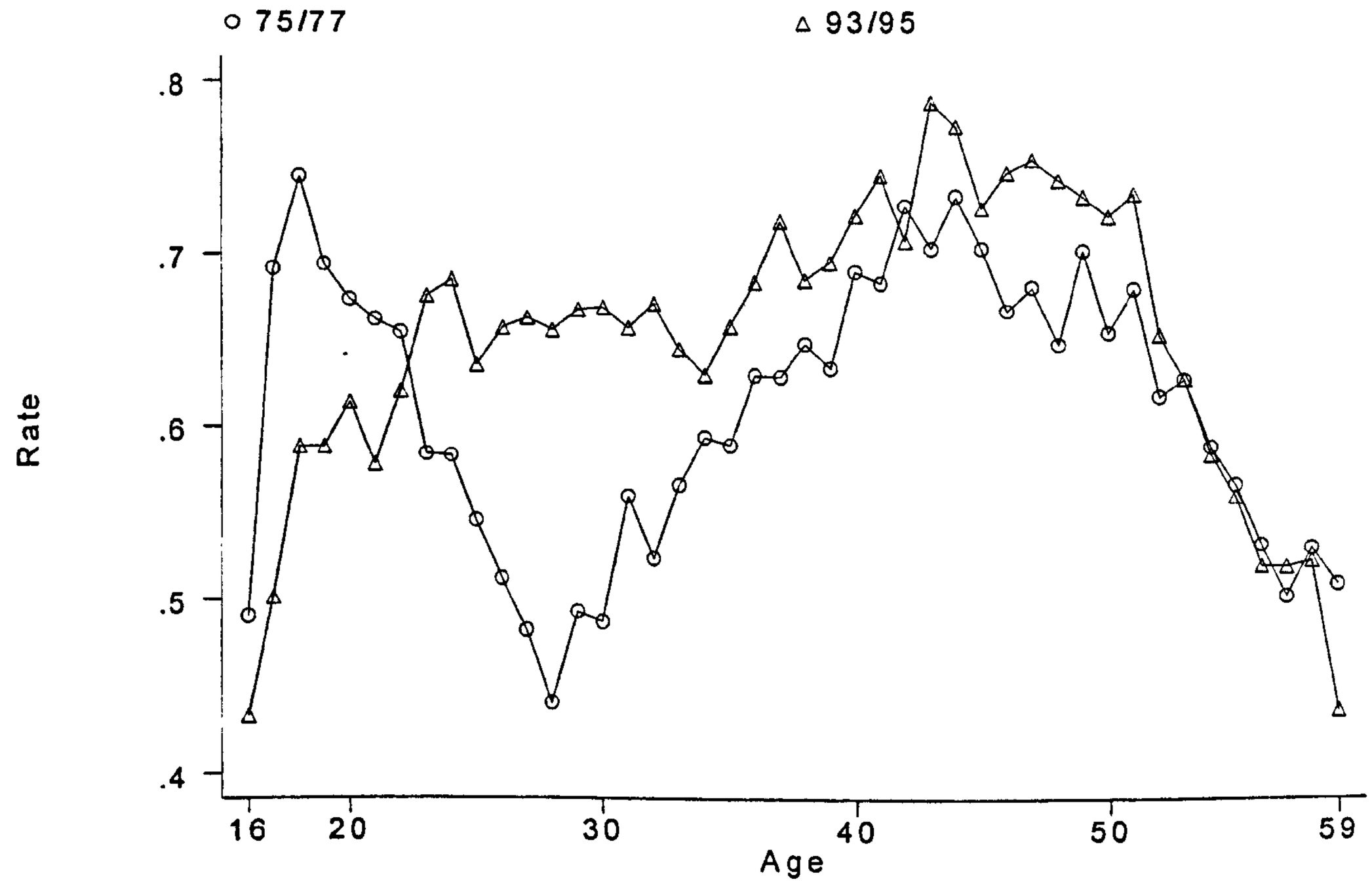
The remainder of this thesis is concerned with the analysis of these issues in more detail within the general framework of a human capital approach, trying to sort out the microeconomic behavioural links between these facts. Models developed in the United States and in the Netherlands offer guides to the nature of the wage returns to work experience and the depreciation of human capital which may take place when workers are out of the labour force. It is these issues with which the thesis is primarily concerned. Chapter 5 analyses the impact of career breaks on wages for a British cohort of women. Chapter 6 provides a fresh insight into the forces at work, which contribute to the gender pay gap. Chapter 7 examines the factors that drive the length of time out and the subsequent return to work. Before then, Chapter 3 describes the principal data sources used throughout the thesis and Chapter 4 gives an introduction to the main theoretical developments in these areas.

Figure 2.1 Employment Rates by Gender

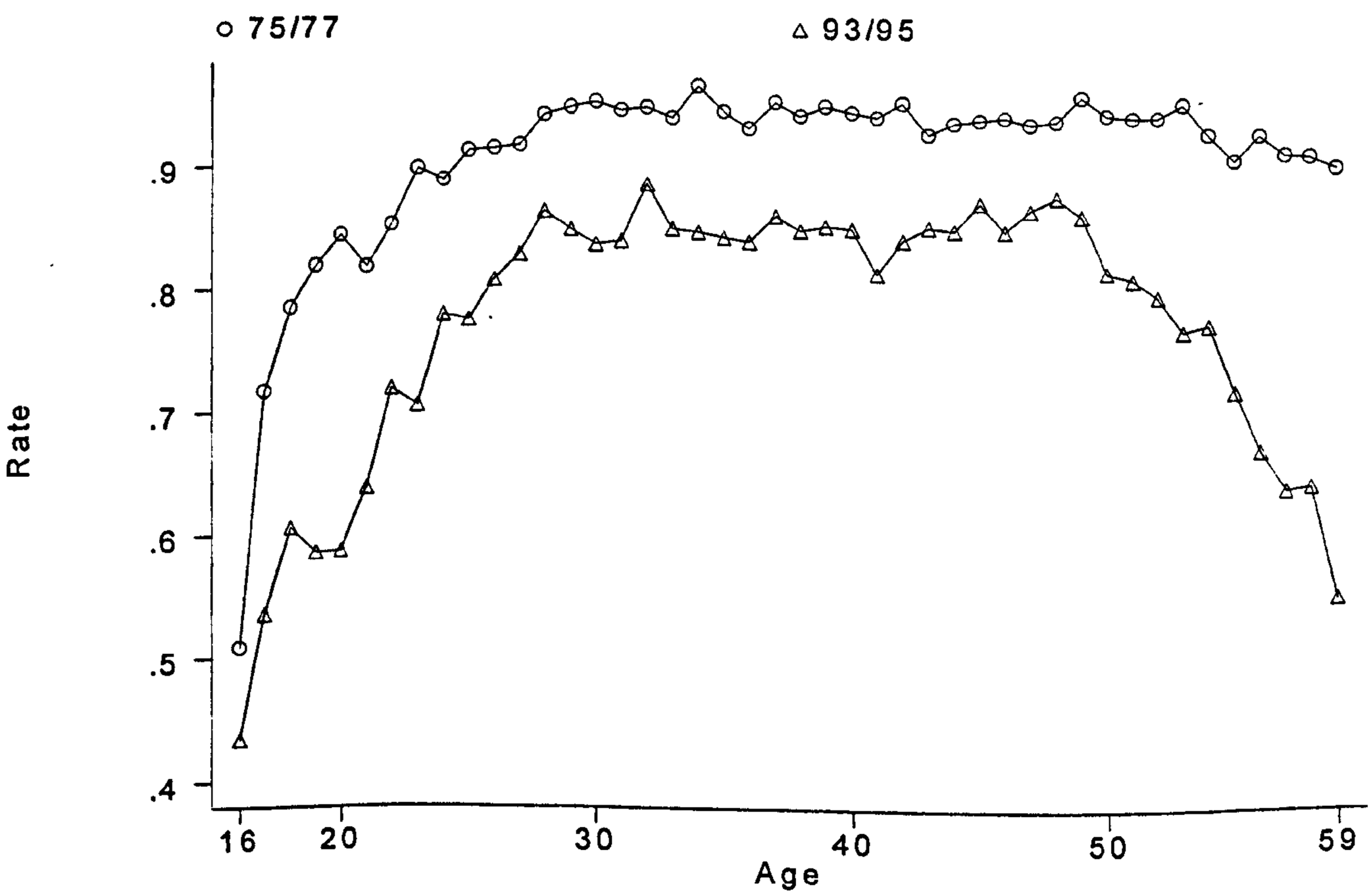
Source: General Household Survey

Figure 2.2 Female and Male Employment Rates by Age

a) Female



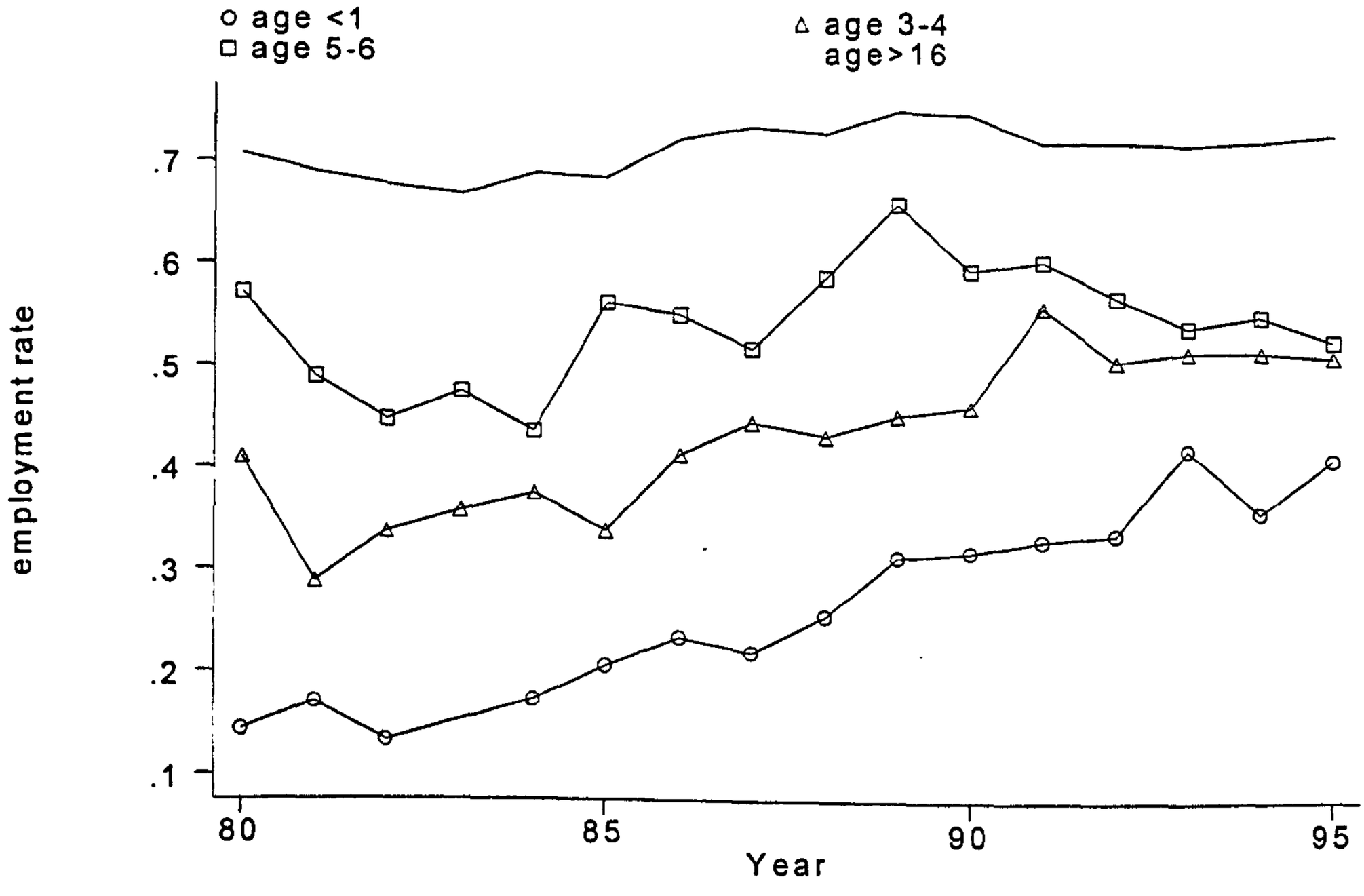
b) Male



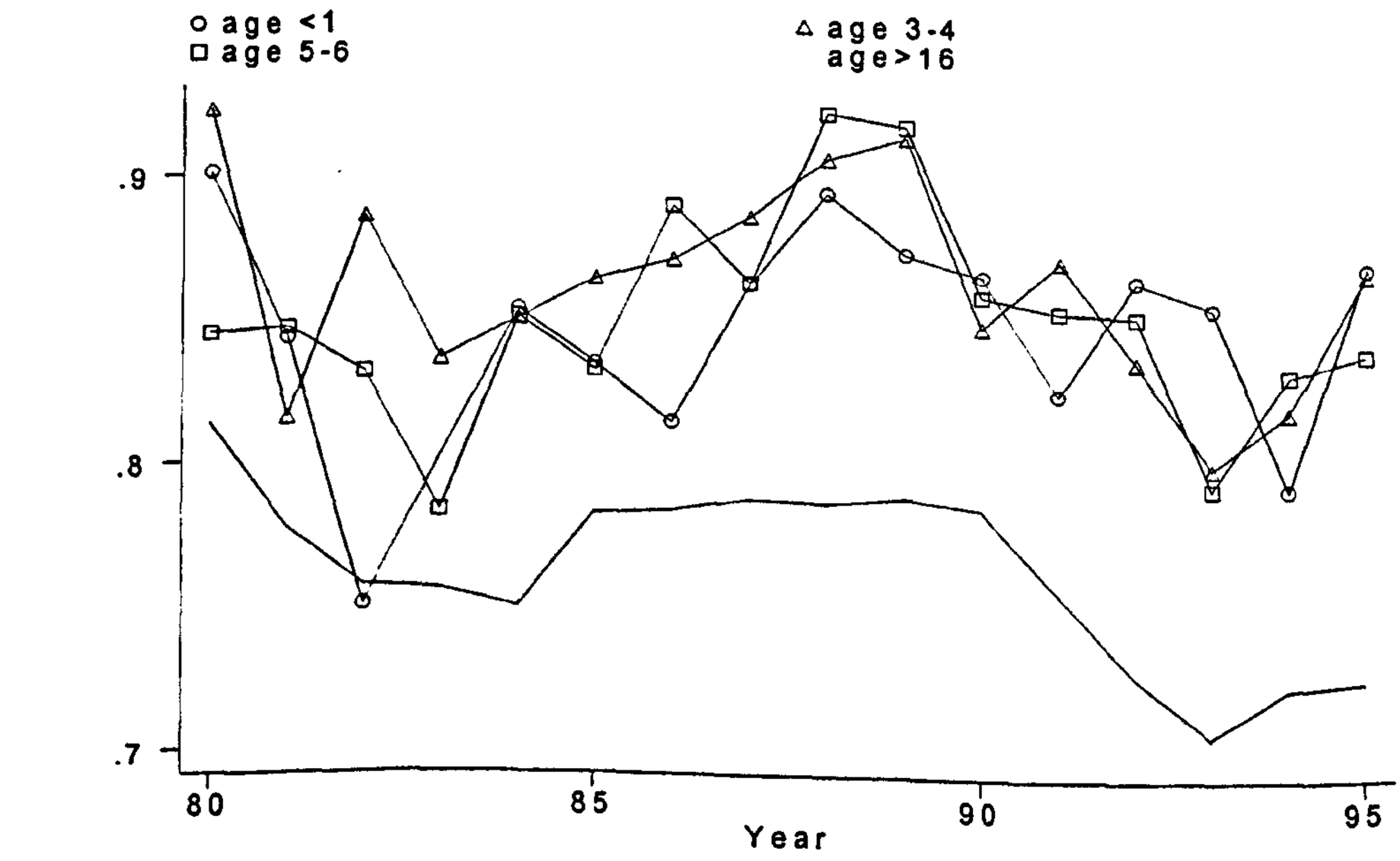
Source: General Household Survey

Figure 2.3 Male and Female Employment Rates by Age of Youngest Child

a) Female



b) Male



Source: General Household Survey

Figure 2.4.a. Weekly Wage Age Profile 1975-95, Women

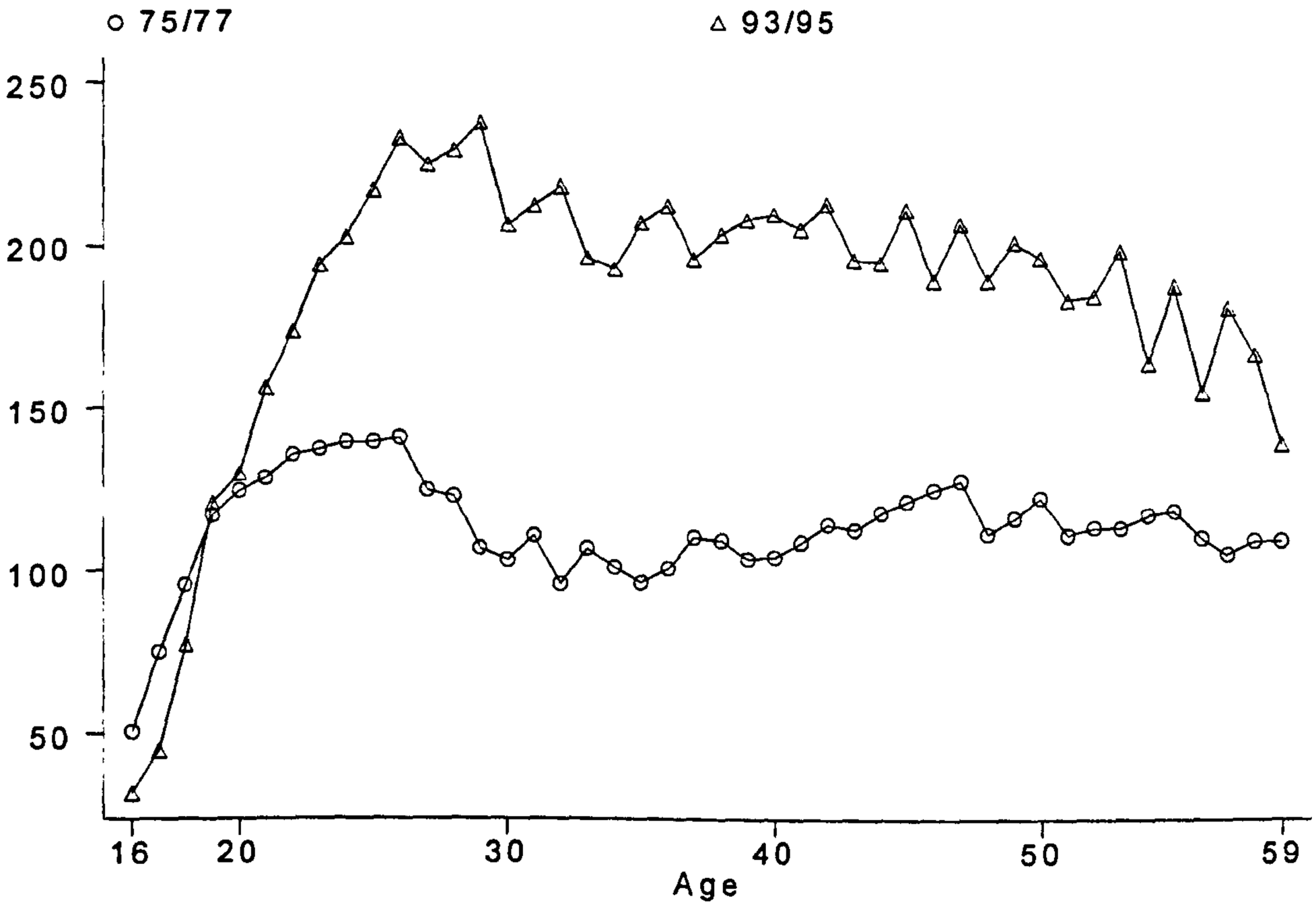
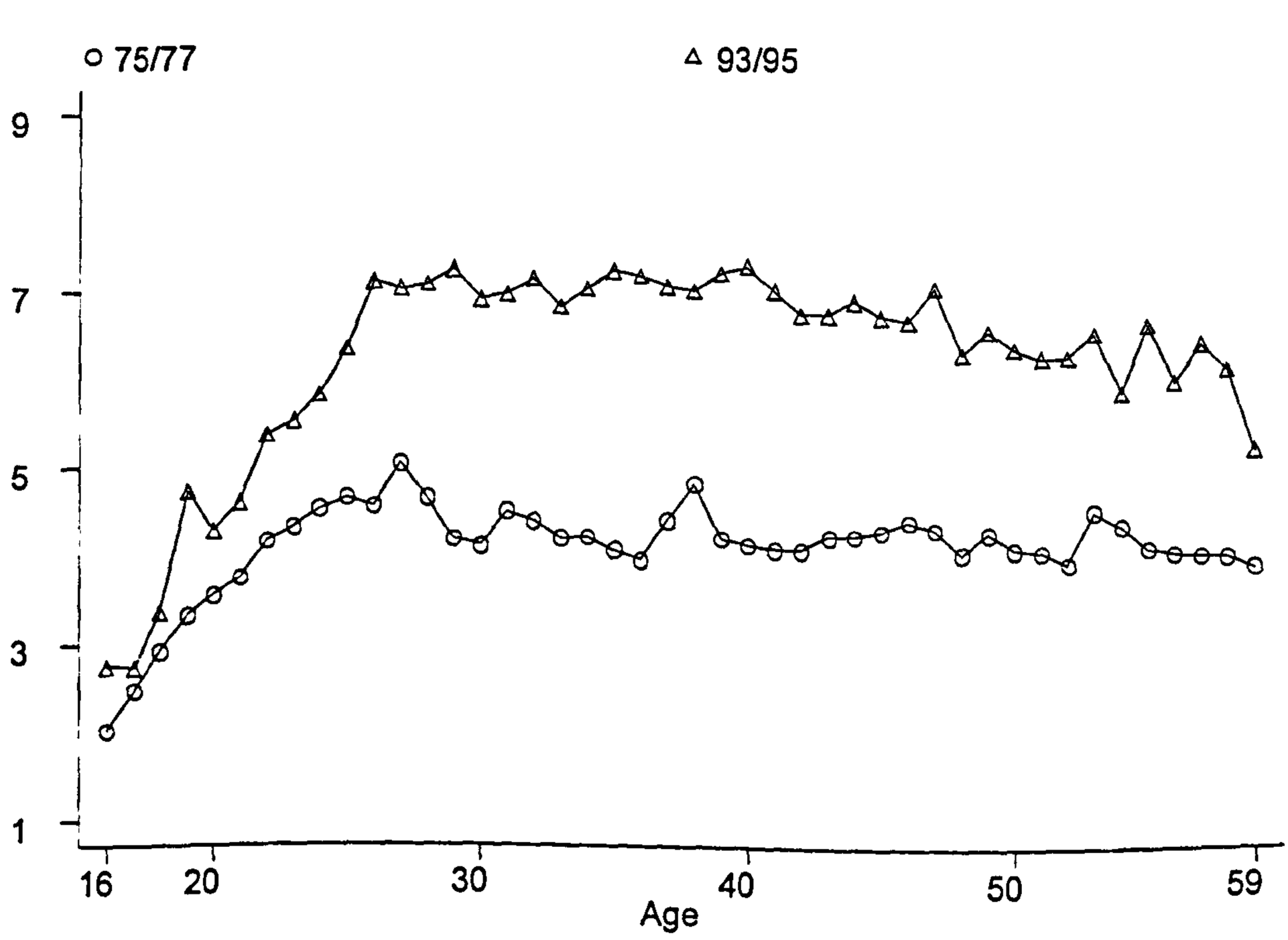


Figure 2.4.b. Hourly Wage Age Profile 1975-95, Women



Source: General Household Survey

Figure 2.5.a. Weekly Wage Age Profile 1975-95, Men

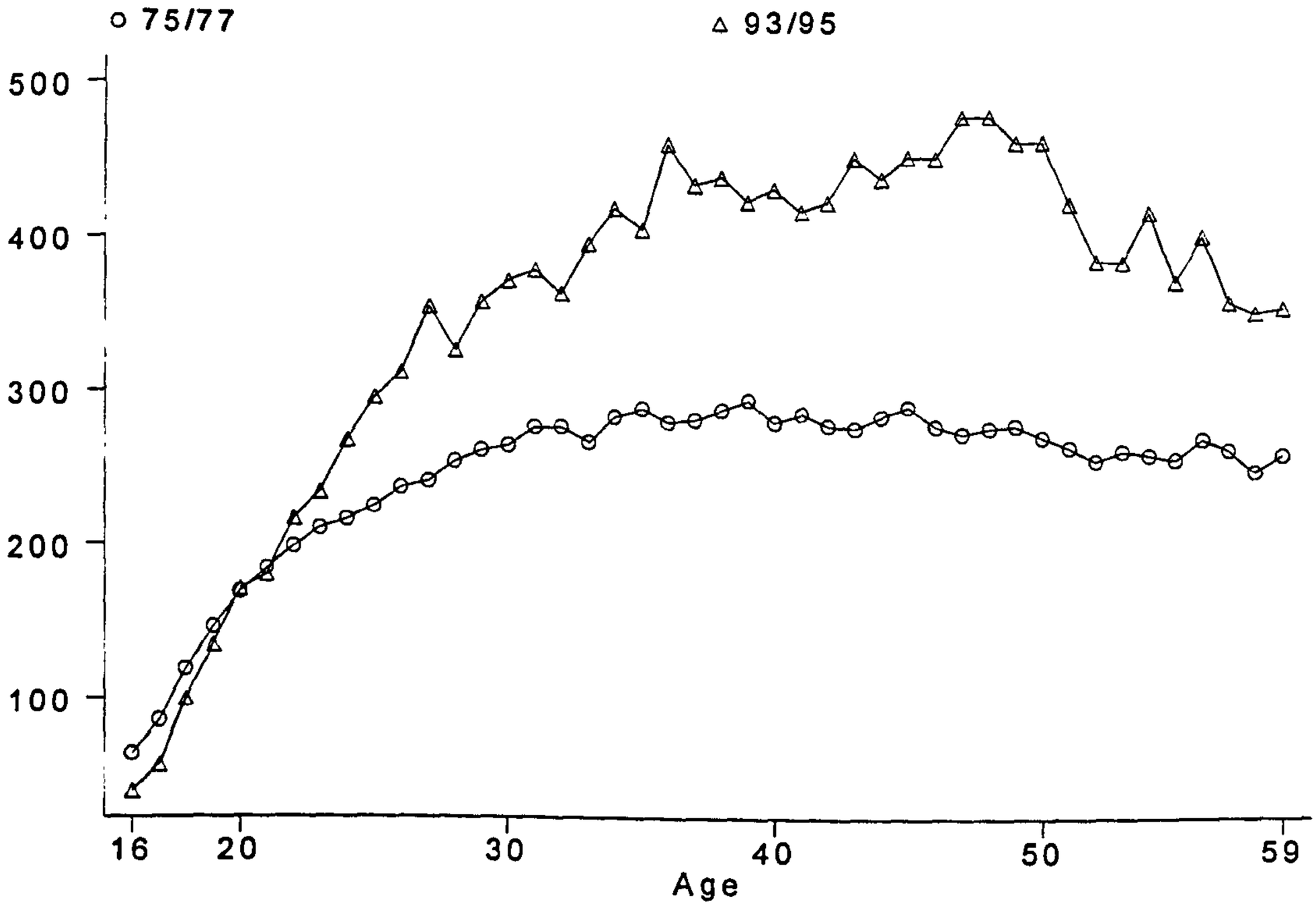
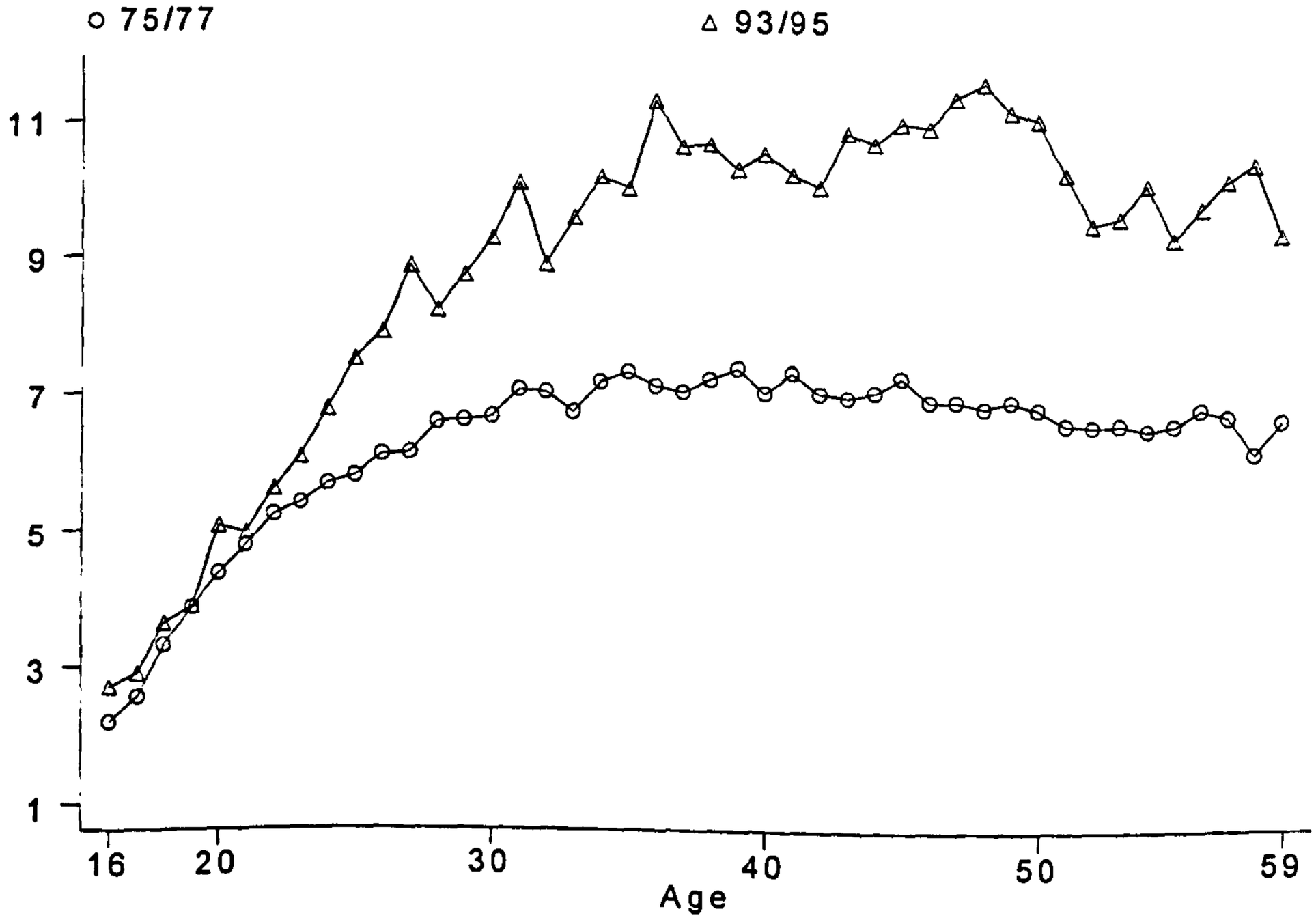


Figure 2.5.b. Hourly Wage Age Profile 1975-95, Men



Source: General Household Survey

Figure 2.6 Hourly Wage by Full- and Part-time Status, 1975-95

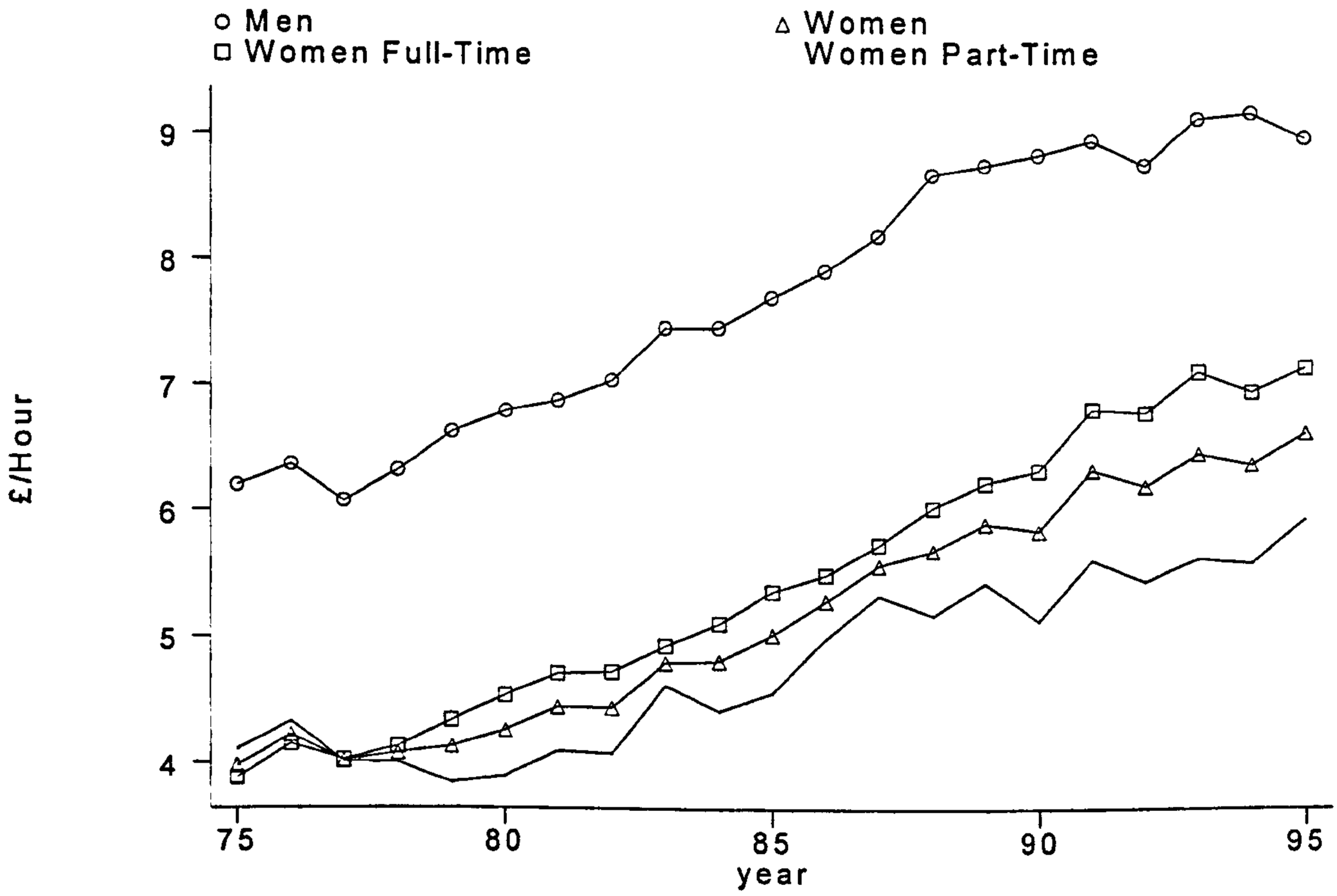
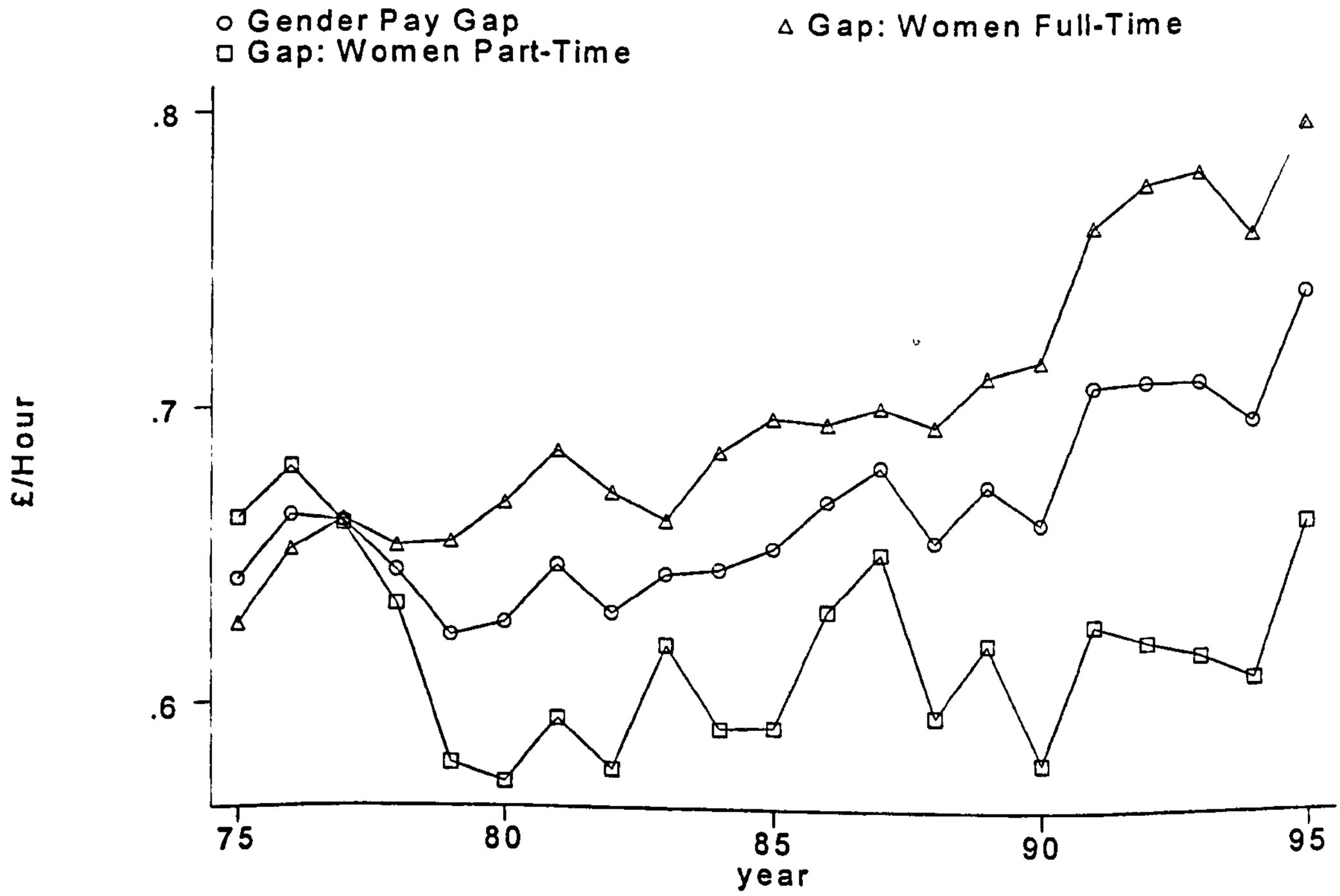


Figure 2.7 Gender Earnings Gap by Full-Time & Part-Time Work, 1975-95



Source: General Household Survey

Figure 2.8 Share of Part-Time Work for Female Employees by Age, 1975-95

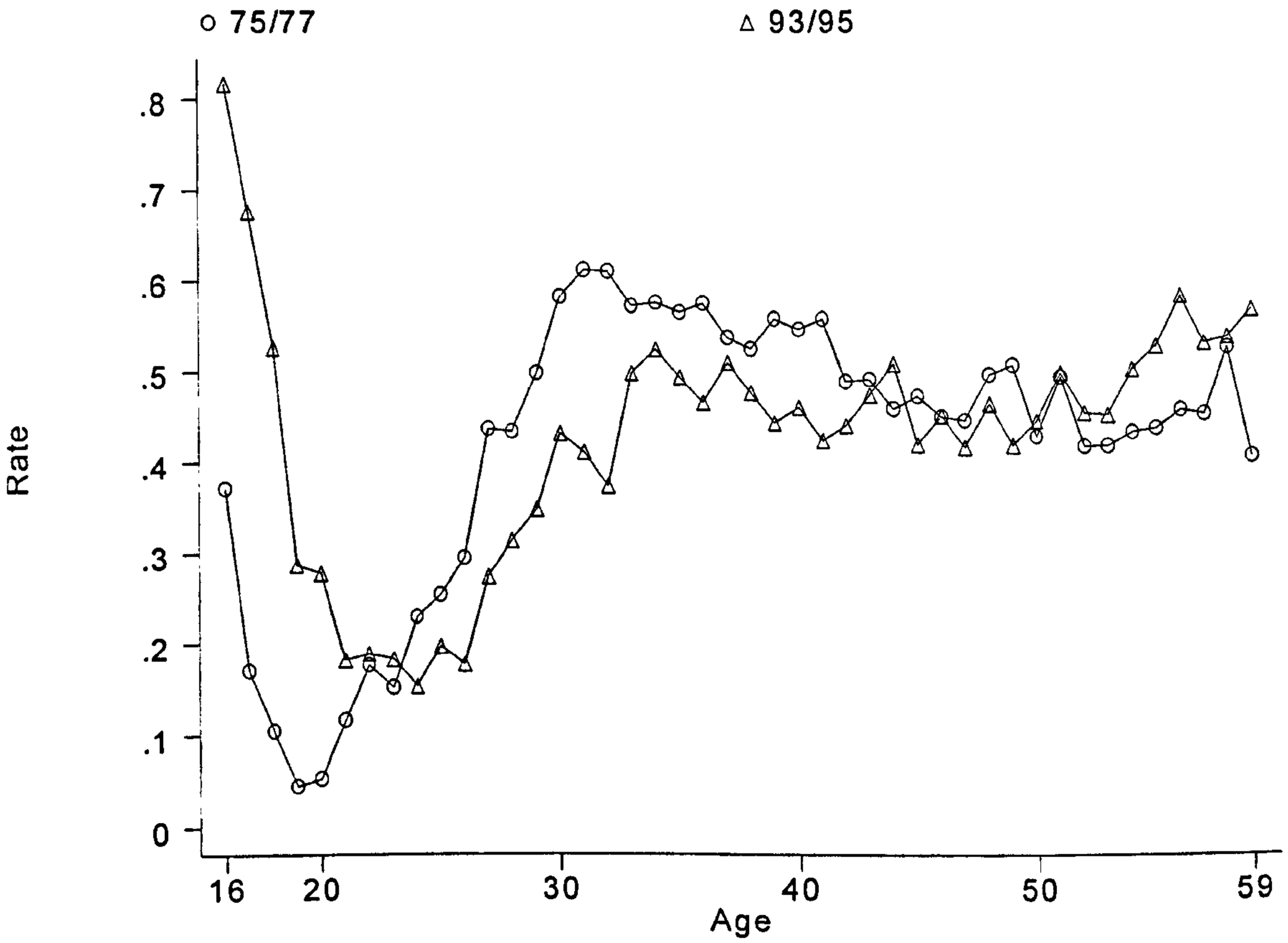
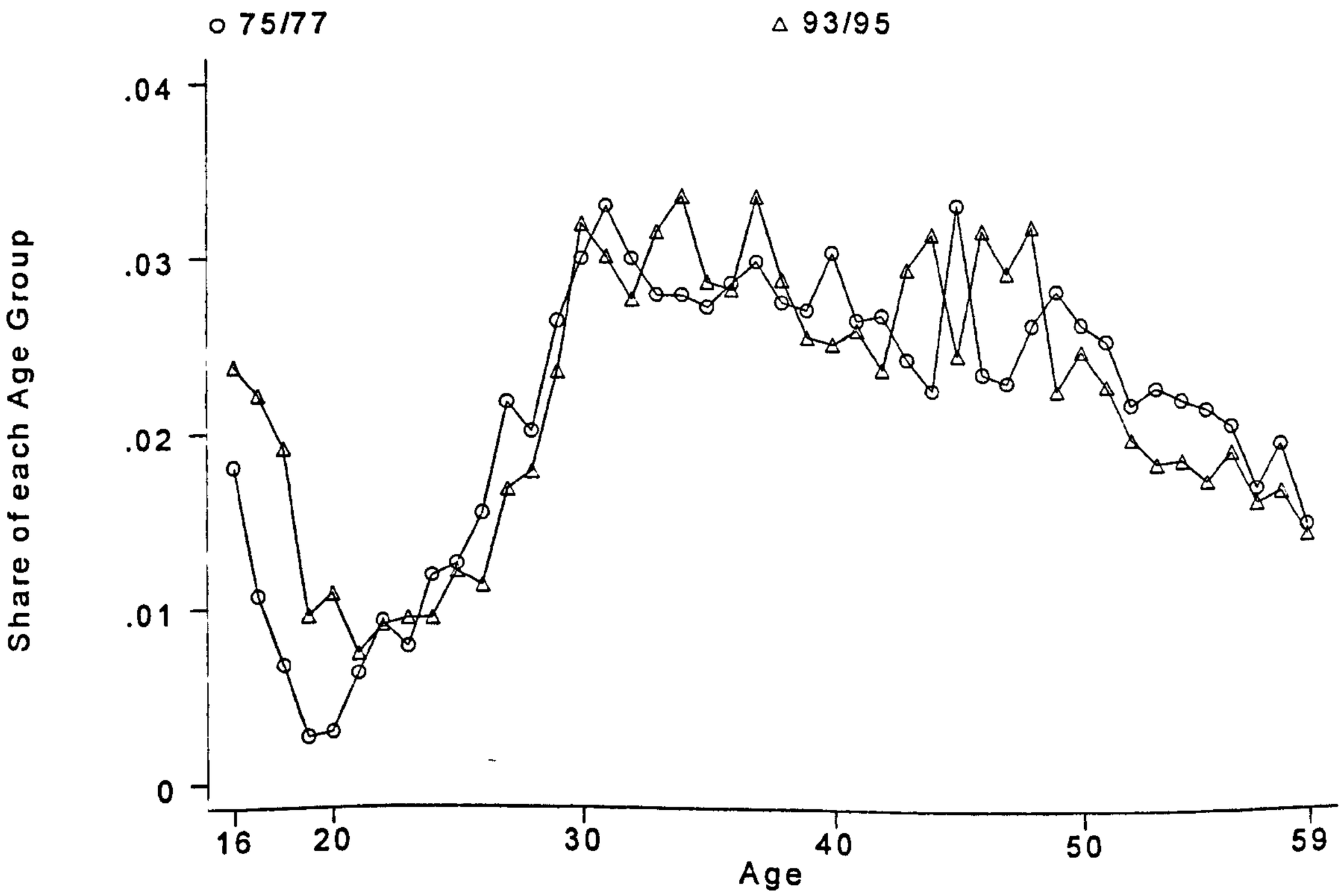


Figure 2.9 Share of Part-Time Work Accounted for by each Age Group 1975/77 & 1993/95 –Women



Source: General Household Survey

Table 2.1 Employment Rates by Gender

Year	*Male*	*Female*	*Total*	*Difference male-female*
1975	.902	.611	.761	+ .291
1981	.798	.572	.687	+ .226
1986	.793	.629	.714	+ .164
1991	.784	.659	.723	+ .125
1995	.764	.666	.716	+ .098

Source: General Household Survey

Table 2.2 Female Employment Rates by Age and Year

Age	*Female Employment Rate*					*Male Employment Rate*				
	1975	**1981**	**1986**	**1991**	**1995**	**1975**	**1981**	**1986**	**1991**	**1995**
16	.504	.363	.486	.491	.444	.511	.305	.519	.457	.438
25	.554	.479	.597	.616	.599	.912	.812	.855	.814	.784
35	.601	.566	.613	.701	.643	.948	.866	.904	.880	.846
40	.671	.702	.713	.712	.714	.938	.902	.925	.879	.862
45	.700	.688	.758	.752	.725	.935	.861	.885	.861	.867
50	.676	.661	.697	.726	.75	.937	.877	.837	.821	.811
55	.581	.551	.583	.571	.562	.911	.807	.795	.744	.743

Source: General Household Survey

Table 2.3 Female Employment Rates by Gender and Age of Youngest Child

	Female Employment Rate			
	1981	**1986**	**1991**	**1995**
No Children	.689	.725	.721	.730
Child aged under				
1	.170	.235	.330	.410
4	.288	.415	.559	.512
6	.522	.554	.648	.512

Source: General Household Survey

Table 2.4 Mean Real Hourly Wages by Gender and Year

	Mean Hourly Earnings						
Year	**Male**	**Female**	**Female FT**	**Female PT**	**Female/ Male Gap**	**FT/Male Gap**	**PT/Male Gap**
1975	6.20	3.98	3.88	4.10	.64	.63	.66
1980	7.00	4.36	4.61	4.02	.62	.66	.57
1981	7.18	4.53	4.78	4.22	.63	.67	.59
1986	7.89	5.28	5.49	4.98	.67	.70	.63
1991	8.97	6.31	6.83	5.87	.70	.76	.65
1995	8.98	6.63	7.15	5.94	.74	.80	.66

Source: General Household Survey.

Table 2.5. Share of Part-Time Work Among Female Employees by Age, 1975-95

	Age						
	Total	**16**	**20**	**30**	**40**	**50**	**55**
Female							
1975/77	.41	.37	.05	.58	.55	.43	.43
1993/95	.42	.82	.27	.41	.46	.44	.53
Share in Total							
1975/77	100	.018	.004	.031	.031	.027	.021
1993/97	100	.024	.011	.030	.025	.025	.018

Source: General Household Survey.

Table 2.6 Female Mean Real Hourly Earnings by Age of Youngest Child

	Hourly Earnings				
	1980	**1981**	**1986**	**1991**	**1995**
All Women					
Child under 1	4.80	4.86	7.10	6.87	7.97
Child under 4	3.98	4.94	5.47	5.19	6.51
Child under 6	3.67	4.01	5.39	5.37	5.92
0 Children	4.56	4.76	5.31	6.73	7.04
Women Part-Time					
Child under 1	4.86	4.82	6.82	6.22	7.50
Child under 4	3.81	4.73	5.14	4.80	5.70
Child under 6	3.61	3.90	5.50	4.87	5.25
0 Children	4.06	4.36	4.86	6.32	6.55

Source: General Household Survey.

Table 2.7 Share of Female Part-time Jobs by Age of Youngest Child

Year	*Share of Part-Time Jobs*			
	Age of Child			
	No children	**1**	**4**	**6**
1980/82	.27	.54	.78	.77
1993/95	.28	.48	.67	.68

Source: General Household Survey.

Chapter 3
Guide to the Principal Data Sets Used in this Thesis

3.1 Introduction

This thesis is primarily an empirical investigation of the changing position of women in the British labour market. In order to pursue these issues, we draw on a variety of household level data sets. This is because there does not exist one single data set that can satisfactorily cover all the aspects that we wish to study. This Chapter provides a brief overview of the data sets, their strengths and limitations, and the construction of the key variables used in subsequent chapters.

3.2 The National Child Development Study Data

Introduction

The data we use in Chapters 5 and 7 draw heavily upon the information contained in the National Child Development Study (NCDS). The NCDS is a longitudinal cohort survey of all children who were born in Britain between 3 and 9 March in the year 1958. There has subsequently been the addition of all those children who were born in the same week outside the country, but who entered Britain before the age of 16. Respondents were then surveyed at the ages of 7, 11, 16, 23 and 33 years. The NCDS has its origins in the study on perinatal mortality (PMS) in 1958. However, the five subsequent NCDS sweeps have taken a more general investigative line. In 1978, information on the performance of cohort members in various public examinations was obtained via contact made with the schools and colleges at which the individual had attended (labelled the EXAMS study.) The survey provides the rare opportunity to study the forces that influence the lives of over 17,000 individuals. The main strength of the study for our purposes is that it contains a detailed break down of each individual's labour market history, from which it is possible to construct measures of actual in-work and out-of-work experience. These can then be matched with each individual's wage performance at the ages of 23 and 33.

Table 3.1 shows the precise sample size in each of the five sweeps and indicates the various sources of information about the cohort member. Notice that in the last sweep in 1991, the children of the cohort members were also drawn into the study.

The Sweep 4 survey involved extensive use of the cohort members themselves as a source of information. The individual was consulted by a research interviewer and the work was merged with information obtained in the 1971 and 1981 Censuses. Sweep 5 followed a similar procedure, whereby use was made of an interviewer and self-completion questionnaires for each cohort member, their partner and children. Sweep 5 forms the main source of the data we utilise and an outline of the survey content are contained below. In any survey of this kind, the issue of how representative the sample is, and questions on the response rates, arise. The response rates of Sweep 5 are contained in Table 3.2. From Table 3.2, we can see that the actual sample of individuals available from the Cohort Member interview for analysis in Chapters 5 and 7 is 11,407 individuals, of which around 6,700 are women. Chapters 5 and 7 use only the sample of women.

The "Your life since 1974" section of Sweeps 4 and 5 included a self-completion questionnaire which generates the event and state history data with respect to cohabitation, children, labour market history and housing for the cohort member. The cohort member's partner was given a similar questionnaire. Individuals were asked to state the beginning and end date in years and months of every in-work and out-of-work spell together with the nature of the spell. Thus, it is theoretically possible to say whether any spell of employment was full-time, part-time or self-employed. It is also possible to identify whether any out-of-work spell was spent in unemployment, education or training, sickness, domestic duties or an "other" unspecified category. From the diaries, economic activity variables could potentially be derived for each of the maximum of 216 months during which an individual might have been economically active between 1974 and 1991. This information was then integrated with each individual's pay data, in order to provide the foundation for model estimation in Chapters 5 and 7. Part of the computer program used to undertake this task is given in the Appendix to this Chapter.

However, this task was complicated by the fact that some of the Sweep 5 data was not completely clean before it was deposited with the ESRC Data Archive. During the self-completion work histories, some individuals made errors in the entry of various start and

end dates. Following Joshi and Hinde (1993), missing and inconsistent dates were dealt with by the insertion of the "correct" date. For example, for each job duration, the individual was asked to write the start month and start year of the job followed by the finish month and finish year. Frequently the months were entered in the wrong order, or the complete year and month information was inadvertently swapped round, or the month or year was simply missing.

Such cases were flagged in the data and then a case-by-case investigation of these observations was carried out. By cross-referencing the in-work periods with the not-in-work periods, it was often obvious where mistakes in data entry had occurred (a total of 373 cases). Indubitably, some consistent errors in the self-completion data remain undetected and form part of the measurement error associated with this type of work. It is obvious that the possibility of making an error in the self-completion section was more likely for those individuals that experienced many alternating labour force states. Where the possibility of making an error is greater for those individuals who have experienced transitions between different labour force states, there is the unfortunate result that this group may have reduced representation. This is a serious limitation in the use of this data set.

For the remaining sample, a total work experience variable was computed that was the sum of each individual work spell across the entire history. All total spells exceeding the maximum possible potential work experience length at age 33 (that is those exceeding the value of age minus age left school), were removed. A similar exercise was performed to construct the total length of spell spent out of work. The NCDS comes complete with a variable which indicates the total number of jobs held by a cohort member by the year 1991. However, no such variable exists for the total number of non-work spells. We computed a tally by deriving which non-work end date was the latest. Having pinpointed the date of the last non-work spell, we were then in a position to calculate the total length of work time both before and after the associated spell. In order to ensure consistency of these before and after break work spell variables, we restricted our post-break work spell variable to be equal to the difference between the total work spell and the pre-break work spell, (following the recommendation of Brown and Light (1992)). Those women with no spells out of work were gathered into the pre-

break category. In a similar procedure, given the information on whether the job as full- or part-time, the total amount of full- and part-time work experience before and after a non-work spell were constructed.

In the "Your Life" section of NCDS Sweep 5, individuals were asked to give information on their usual take home pay (after tax and other deductions, but including overtime and bonuses). They were subsequently asked to say for which time period this wage was paid and whether this was their usual hours for a typical week. From this, we have calculated the gross weekly and hourly wage variable and we indexed this to January 1992 prices to create the real variables used throughout study.[1] In the pay data section, some cohort members may have recorded an incorrect wage or incorrect pay period. We remove all those earning less than 50 pence and greater than £150 an hour. The final sample of women who have complete information on wages, job history and other characteristics used in the analysis is around 4, 700.

The cohort member interview was designed to obtain in-depth information about both the individual's and their partner's jobs, unemployment, education and training, qualifications, cohabitation, children, housing, health, income and citizenship. The NCDS enables us to calculate the calendar time when events such as educational qualifications, birth and marriage occurred. This information is then used to provide the vector of characteristics of the women at the point of re-entry to work as used in Chapter 7.

One in three cohort member families was given a mother and child survey which consisted of an interview carried out with the mother figure and the child of the family. During the mother interview, questions on health and the schooling experience were aimed at the relevant female. In the child-orientated section of the mother interview, questions were geared to the all-round development of the child of the family. During the child interview, the interviewers carried out nine age-specific child assessments. Tests to assess the performance in reading, mathematics and English of the cohort member at the ages of seven and eleven were also been obtained in Sweeps 2 and 3. We use the results of these tests in Chapter 5.

To conclude, the NCDS data set provides the largest and probably the most detailed source of labour market history on a sample of British women. As such, it is a useful starting point to examine the issues in this thesis.

3.3 British Household Panel Survey Data

Chapter 6 uses the first five waves of the British Household Panel Survey (BHPS) covering the years 1991-95. This covers a period of recession in which unemployment peaked in 1993 followed by a period of recovery. The BHPS is a household-based panel survey consisting initially of some 5,500 households and 10,300 individuals drawn from 250 different areas of Britain who are interviewed every autumn. To date, eight waves of the survey have taken place with the fieldwork for the data having been sub-contracted by the ESRC Research Centre on Micro-Social Change (at the University of Essex) to a research agency. When this thesis was written, only the first five waves were available. The geographical area for the survey incorporates areas of England and Wales and areas of Scotland south of the Caledonian Canal. The Postcode Address File was used to generate the sample, which coves all non-institutional residences. The continuing representativeness of the survey is ensured (and loss of panel members minimised) by following panel members wherever they move in the UK and including in the panel the new members of households formed by original panel members, (see Table 3.3). All children are interviewed when they reach the age of sixteen.

The special nature of the BHPS lies in its development as a panel study, which enables researchers to analyse the dynamic effects of socio-economic changes. One of the closest cross-sectional data sets to the BHPS is the General Household Survey (see below), but in addition to the panel aspect, the BHPS is superior to the GHS in its incorporation of questions on intra-household decision-making and attitudinal values. However, the sample size of the BHPS has meant that the level of disaggregation has not been as extensive as some of the other national surveys. The questionnaire is split into five sections. Namely, the household composition component and the household, the individual, the self-completion and the proxy sections. We have used information derived from the individual questionnaire encompassed in the section entitled "Current

[1] All wage variables are deflated throughout this thesis as we carry out various longitudinal analyses.

Employment". This section asks about wages currently received and wages gained last year. Details on labour market status and other characteristics are recorded around a reference point of September 1st in each year along with wage data for every new spell in the 12 months between September last and the current interview date. In Wave 2 of the survey, a retrospective history of marriage (and cohabitation), fertility and employment transitions (in the "Employment History" section) were collected. Wave 3 provided a more detailed lifetime job history which could have, in principle, been developed to provide a comprehensive work experience measure similar to the one we derived for the NCDS. However, our main aim in using the BHPS was to focus on the issue of labour market entrants and wage growth. Thus it was sufficient for our needs to pinpoint whether a woman had re-entered the labour market within the previous twelve months.

In Chapter 6, we restrict our attention to employees and use average hourly wages including overtime as our wage measure. In the "Living in Britain" Individual Questionnaire of BHPS, individuals were asked to give information on their take-home pay (after tax, National Insurance, pensions and union dues) for the last time they were paid. They were subsequently asked to say for which time period this wage was paid and whether this was their usual take-home pay. From this, we have constructed hourly wages. These hourly wages were deflated using the average weekly earnings and weekly hours indices, so that the average wage on our measure should be constant over time. To be part of the computation of wages an individual must have been in employment either now or previously but the decomposition of average wages which we use also requires the availability of other information which further restricts our sample. The definition of part-time work was derived if the individual had a working week of less than 30 hours a week. In conclusion, we note that the overriding strength of the BHPS is its panel aspect, a point which we exploit fully in Chapter 6.

3.4 General Household Survey

The General Household Survey is now a biennial survey carried out in every month of the year by the Office of Population Censuses and Surveys, based on a sample of the population living in private (post-coded) households.

The Survey began in 1971 and, until 1996/97, it was carried out annually. It covers around 10,000 households. Each member aged 16 and over in the household is interviewed. The survey has around a 66 per cent response rate. Certain subjects are only covered from time to time and the GHS Annual Reports include a summary of the main topics covered for that year. The GHS is the only nationally representative data set which contains, amongst the other information that we require, wage data over a consecutive twenty-two year period. However, as with the BHPS, the earnings data sample is comparatively small, at around 8,000 men and women each year.

The GHS provides us with the data necessary to estimate the potential entry wage of our sample of NCDS women between the years 1981 and 1991 in Chapter 7, and the entry wage pay gap in Chapter 6. Between 1979 and 1991, the GHS contained retrospective data on the individual's labour market status one year prior to sampling. A woman is pinpointed as an entrant if she was in work at the time of interview but she was not previously in work according to the retrospective question. This information is then matched to the women in the NCDS sample who are identified as returning to work after having time out. The GHS further served our need for an introductory overview of labour market developments in Chapter 2. As with both the NCDS and the BHPS, the wage variable was derived from the responses individuals gave on questions on their usual take home pay (after tax and other deductions but including overtime and bonuses). They were subsequently asked to say for which time period this wage was paid and whether this was their usual hours for a typical week. From this, we have calculated the gross weekly and hourly wage variable and indexed this to April 1998 prices to create the real variables used in Chapter 2. The GHS was also used to generate information on part- and full-time earnings where the definition of part-time work was derived from a working week of less than 30 hours a week.

3.5 Labour Force Survey

The Labour Force Survey (LFS) provides the most comprehensive source of labour market information in the UK. It is a nationally representative sample of around 60,000 households which is then weighted in order to permit population estimates. The survey

has been carried out on a quarterly basis since 1992 and households are kept in the survey for five consecutive quarters. There was no information on pay before 1992. Pay information is collected in the fifth (and last) wave of a household's participation. The very first interview takes place with an interviewer but subsequent interviews are usually carried out by telephone.

Earnings information from the LFS are sometimes less accurate than employer-based information, such as the New Earnings Survey, especially where responses are obtained from proxy respondents (some 30 per cent of responses), but the LFS is much larger than any other corresponding British household data set. Hourly pay estimates from the LFS can only be derived from questions relating to the last usual pay amount and the relevant pay period. Workers in the low wage sectors who do not regularly receive a pay slip tend to understate pay levels and this limitation is exacerbated by the omission of any bonus payments in the LFS. Further, there exists disparities between employer and employee estimates of the number of hours worked. We use the LFS to provide the estimates of the change in the entrant shares amongst employees over time in Chapter 6. Here, entrants are defined, as with the GHS, on the basis of a retrospective labour market status question.

3.6 New Earnings Survey

The New Earnings Survey (NES) was conceived in 1970 with the objective of being the primary source of earnings information for employees in employment in the UK. The data is derived from employer payroll information for around 160,000 cases and the survey has been carried out in April of each year since 1970. The richness of the data set comes from its ability to provide information on fine degrees of occupational, industrial and regional breakdowns.

The survey is based on a 1 per cent sample of employees, where the sample is obtained from workers whose National Insurance (NI) number ends with a specific pair of digits. Around 90 per cent of the sample is identified by the Inland Revenue who are able to pinpoint the relevant employer once the NI number has been selected. Therefore, a condition of selection is that pay-as-you-earn records exist for the individuals. The rest of the sample is obtained straight from large employers who incorporate employees with

the relevant NI numbers in their organisation. This enables some workers to be included in the sample whose earnings are below the tax threshold. At the time of origin, part-time employment played a far less significant part in the UK labour market.

However, the NES is known to be deficient in five main areas. First, small firms (less than 50 employees) are under-represented. Small businesses have a higher mortality rate than larger ones and this, coupled with the tendency to follow up non-response in firms with large number of employees, contributes to the lack of representativeness of the data. Second, the NES data provides only a small amount of demographic information. Third, there exists the obvious under-coverage of employees below the pay-as-you-earn thresholds. The bulk of those that are missed are workers in part-time employment. Fourth, workers who have recently moved jobs are far more likely to be omitted from the data. Chapter 6 focuses in part on this group of people and so this qualification should be borne in mind. Lastly, the use of hourly wages in the NES data can only occur if information is given on the hours of work for those who were present in the sampling period. For the most part, we use the NES to provide an insight into the behaviour of low-paid part-time men and women in contrast to their full-time counterparts, and there is some evidence that the former are under-represented in the NES.

Conclusion

In conclusion to this Chapter on data, we note that access to these data sets has been facilitated by the existence of the national on-line service at Manchester University and the increased flexibility of new software packages such as STATA© on which most of the subsequent analysis was undertaken. Finally, we note that Table 3.4 summarises the use of the various data sets in this thesis, along with their major advantages for our purposes.

Table 3.1 National Child Development Study Sweeps

Survey	*PMS 1958*	*NCDS1 1965*	*NCDS2 1969*	*NCDS3 1974*	*EXAM 1978*	*NCDS4 1981*	*NCDS5 1991*
Age	Birth	7	11	16	20	23	33
Target sample	17 733	16 883	16 835	16 915	16 906	16 457	15 600
Source of information	Parents Medical	Parents School tests Medical	Parents School Tests Medical Cohort member	Parents School Tests Medical Cohort member Census	School	Cohort member Census	Cohort member Partner Children
Actual sample	17 414	15 468	15 503	14 761	14 370	12 537	11 400

Source: NCDS5: A Brief Outline by the Social Statistics Research Unit (1995) City University

Table 3.2 NCDS Sweep 5 Response Rates

Survey instrument	*Target*	*Traced*	*Obtained*	*Percentage response rate*
Cohort Member Interview	15 666	13 444	11 407	85
Cohort Member Your Life Section	15 666	13 444	11 175	83
Cohort Member What Do You Think Section	15 666	13 444	10 898	81
Partner Interview		9 138	7 126	82
Your Life Mother Interview		2 556	2 524	99
Mother Interview Your Child Section		5 067	5 012	99
Child Interview Tests Section		3 575	3 467	97

Source: Social Statistics Research Unit (1995)

Table 3.3 British Household Panel Survey Sample Sizes

Wave	*One*	*Two*	*Three*	*Four*	*Five*	*Six*	*Seven*
Number of full /proxy /telephone interviews	10,264	9,845	9,600	9,481	9,249	9,440	9,373
Number of households	5,538	5,227	5,228	5,125	5,034	5,066	5,025
Wave on wave re-interview rate (%)	NA	87.7	90.3	94.9	94.8	97.6	97.4

Note: Wave 7 was subjected to the addition of 950 households drawn from the European Community Household Panel which took the number of co-operating households to 5,975.

Table 3.4 Summary of Survey Data Sets

	Benefits	*Limitations*	*Use*
BHPS	Comprehensive panel study	Relatively small sample size prevents disaggregated analysis. Only available since 1991.	Estimation of the dynamics of the pay gaps in Chapter 6
NCDS	Detailed source of labour market history Detailed background information such as ability scores	Job history data required much cleaning Cohort data set	Wage equations in Chapter 5 Survival analysis in Chapter 7
GHS	Detailed, nationally-representative, consistent information on individuals over longest consecutive period of time	Relatively small sample size Less information on workers' characteristics	Overview of labour market in Chapter 2 Entry wage pay gap in Chapter 6 Potential entry wage in Chapter 7
LFS	Much larger than any other British household data set. Detailed information on individual and firm characteristics Panel element since 1992	Earnings data self-reported and less accurate than employer-based data such as the NES	Change in entrant shares in Chapter 6
NES	Large sample Much finer level of disaggregation	Under-representative of small firms Small amount of demographic information Under-coverage of workers who earn less than the PAYE threshold Limited worker characteristics	Long run wage growth in Chapter 6

Appendix 3

Example of Part of the Data Cleaning Process

```
/*
**************************************
This deals with quirky job*spells
before they become totspells
**************************************
*/
replace j10mfi_5=6 if serial=="093238M"
replace nj1yfi_5=91 if serial=="093238M"
replace nj1yst_5=91 if serial=="093238M"
replace nj1mst_5=6 if serial=="093238M"
replace nj2mst_5=. if serial=="093238M"
replace nj2yst_5=. if serial=="093238M"
replace nj2mfi_5=. if serial=="093238M"
replace nj2yfi_5=. if serial=="093238M"

replace j2yst_5=74 if serial=="X83005P"

replace j6yfi_5=89 if serial=="143013L"
replace nj1yst=82 if serial=="143013L"
replace  j7mfi=12 if serial=="143013L"
replace  j7yfi=89 if serial=="143013L"
replace  j8mst=12 if serial=="143013L"
replace  j9mfi=7  if serial=="143013L"
replace  j9mfi=91 if serial=="143013L"
replace  j9yfi=91 if serial=="143013L"

replace nj3mfi_5=8 if serial=="149001L"

replace nj4yfi_5=88 if serial=="200098N"

replace nj6yfi_5=83 if serial=="287141A"

replace nj1mfi_5=7 if serial=="330024J"

replace j1mfi_5=10 if serial=="423032Z"
replace j1yfi_5=76 if serial=="423032Z"
replace j2mst_5=6  if serial=="423032Z"
replace j2yst_5=80 if serial=="423032Z"
replace j2mfi_5=6  if serial=="423032Z"
replace j2yfi_5=84 if serial=="423032Z"
replace j3mfi_5=3  if serial=="423032Z"
replace j3yfi_5=85 if serial=="423032Z"
replace j6yfi_5=91 if serial=="423032Z"
replace nj3mst_5=6 if serial=="423032Z"
replace nj3mfi_5=10 if serial=="423032Z"

replace nj4mfi_5=11 if serial=="481031A"

replace nj2yst_5=90 if serial=="500487X"

replace nj4mst_5=3 if serial=="550323X"

replace nj3yfi_5=81 if serial=="565061B"

replace nj2mst_5=9 if serial=="620138R"
replace nj2yfi_5=82 if serial=="620138R"
```

```
replace nj1yfi_5=75 if serial=="740022R"
replace j1yst_5=74 if serial=="740022R"
replace j5mfi_5=7  if serial=="740022R"

replace nj1yfi_5=88 if serial=="750140D"

replace nj1yst_5=74 if serial=="982062F"

replace j4yst_5=88 if serial=="985045X"
replace nj1yst_5=86 if serial=="985045X"
replace nj1yfi_5=88 if serial=="985045X"

replace nj1yst_5=74 if serial=="987074R"
replace nj1yfi_5=91 if serial=="987074R"

replace nj4yfi_5=91 if serial=="X67013W"

replace nj7mfi_5=8 if serial=="X80054M"

replace j1mfi_5=12 if serial=="050070F"

replace nj2yfi_5=83 if serial=="093257R"

replace  j6mfi_5=6  if serial=="514155Y"

replace  j1yst_5=73 if serial=="581010Z"
replace  j1mfi_5=8  if serial=="581010Z"
replace  j2mst_5=8  if serial=="581010Z"
replace  j2yst_5=73 if serial=="581010Z"
replace  j2mfi_5=1  if serial=="581010Z"
replace  j6yst_5=82 if serial=="581010Z"
replace  j6yfi_5=84 if serial=="581010Z"
replace  j7yfi_5=86 if serial=="581010Z"
replace  j8yst_5=86 if serial=="581010Z"
replace  j8yfi_5=88 if serial=="581010Z"
replace  j9yst_5=88 if serial=="581010Z"
replace  j9yfi_5=90 if serial=="581010Z"
replace  j10yst_5=90 if serial=="581010Z"
replace  j10yfi_5=91 if serial=="581010Z"
replace  j7yst_5=84 if serial=="581010Z"
```

and so on.

```
/*
**************************************
THIS PART DEALS WITH QUIRKY NO JOB* SPELLS
**************************************
*/
replace nj1yfi_5=75 if serial=="048027S"

replace  j1yst_5=75 if serial=="087006D"
replace nj1yfi_5=75 if serial=="087006D"

replace  j2yfi_5=90 if serial=="110170S"
replace  j3yfi_5=90 if serial=="110170S"
replace nj1mst_5=2  if serial=="110170S"

replace nj1yfi_5=82 if serial=="384013H"
replace nj2yst_5=82 if serial=="384013H"

replace  j2mst_5=5  if serial=="385028B"
```

```
replace nj1mfi_5=7  if serial=="385028B"
replace nj1yfi_5=74 if serial=="385028B"

replace nj1yst_5=76 if serial=="421029A"
replace j10mfi_5=1  if serial=="421029A"
replace j10yfi_5=90 if serial=="421029A"

replace nj2mfi_5=12 if serial=="183018X"

replace  j2mfi_5=2  if serial=="183031P"
replace nj2mst_5=2  if serial=="183031P"

replace nj2mst_5=9  if serial=="286019Y"
replace j10yst_5=91 if serial=="286019Y"
replace nj1yst_5=76 if serial=="286019Y"
replace nj1yfi_5=77 if serial=="286019Y"
replace nj2yst_5=77 if serial=="286019Y"
replace j10mst_5=5  if serial=="286019Y"

replace nj2yst_5=77 if serial=="330093D"
replace nj2yfi_5=79 if serial=="330093D"

replace nj2mst_5=12 if serial=="425035S"
replace nj2yst_5=76 if serial=="425035S"
replace nj2mfi_5=7  if serial=="425035S"
replace nj2yfi_5=77 if serial=="425035S"

replace nj5yfi_5=90 if serial=="041006V"
```

and so on.

```
/*
**********************************************
This deals with months and year missings
**********************************************
*/

replace j1yst_5=74 if serial=="010183U"

replace j1yst_5=74 if serial=="046024Z"

replace j1yst_5=73 if serial=="083054U"

replace j1yst_5=73 if serial=="088019U"
replace j2yst_5=73 if serial=="088019U"

replace j1yst_5=74 if serial=="092110C"

replace j1yst_5=73 if serial=="120106P"

replace j1yst_5=74 if serial=="130005P"

replace j1yst_5=74 if serial=="181022B"

replace j1yst_5=74 if serial=="182047Z"

replace j1yst_5=74 if serial=="187028X"
replace j3mfi_5=6  if serial=="187028X"

replace j1yst_5=74 if serial=="200046S"
```

```
replace j1yst_5=73 if serial=="213006B"

replace j1yst_5=73 if serial=="220003L"

replace j1yst_5=73 if serial=="230017D"

replace j1yst_5=74 if serial=="280031E"

replace j1yst_5=74 if serial=="284020W"

replace j1yst_5=74 if serial=="380013L"

replace j1yst_5=73 if serial=="381099E"

replace j1yst_5=74 if serial=="384024N"

replace j1yst_5=74 if serial=="400051Z"

replace j1yst_5=73 if serial=="422049N"

replace j1yst_5=74 if serial=="465018T"

replace j1yst_5=74 if serial=="511036Y"

replace j1mfi_5=1  if serial=="228003D"
replace j1yst_5=74 if serial=="228003D"
replace j1mst_5=6  if serial=="228003D"
replace j3mfi_5=6  if serial=="228003D"

replace j1mfi_5=6  if serial=="450009J"

replace j1mst_5=6  if serial=="510167K"
replace j1yst_5=73 if serial=="510167K"
replace j1mfi_5=12 if serial=="510167K"

replace j1mst_5=6  if serial=="513127N"
replace j1yst_5=74 if serial=="513127N"
replace j1mfi_5=1  if serial=="513127N"

replace j1yfi_5=79 if serial=="092283M"
replace j1yst_5=74 if serial=="092283M"
replace j2yst_5=79 if serial=="092283M"

replace j2yst_5=90 if serial=="211011J"

replace j1mfi_5=11 if serial=="431026A"
replace j1yfi_5=79 if serial=="431026A"
replace j2mst_5=2  if serial=="431026A"
replace j2yst_5=80 if serial=="431026A"

replace j3mfi_5=6  if serial=="047026K"

replace j3mfi_5=6  if serial=="055065R"

replace j3mfi_5=6  if serial=="280054T"

replace j3mfi_5=1  if serial=="289178M"
replace nj1mfi_5=6  if serial=="289178M"

replace  j3mfi_5=1  if serial=="500565R"
replace  j3yfi_5=78 if serial=="500565R"
```

```
replace  j4yst_5=78 if serial=="500565R"
replace  j4mst_5=1  if serial=="500565R"
replace  j4mfi_5=1  if serial=="500565R"
replace  j4yfi_5=79 if serial=="500565R"
replace  j2yfi_5=77 if serial=="500565R"

replace  j3mfi_5=6  if serial=="515069M"

replace  j4mfi_5=6  if serial=="186122J"

replace  j4mfi_5=6  if serial=="482053S"

replace  j4mfi_5=6  if serial=="514046T"

replace  j5mst_5=.  if serial=="095011S"

replace  j5yst_5=84 if serial=="308017L"

replace nj2mfi_5=1  if serial=="280103D"
replace  j5mfi_5=6  if serial=="280103D"

replace  j5mfi_5=6  if serial=="282055F"

replace  j5mfi_5=6  if serial=="308010V"

replace  j5mfi_5=3  if serial=="381047K"

replace  j7mfi_5=1  if serial=="110266F"

replace  j11yfi_5=.  if serial=="050070F"
replace  j12mst_5=.  if serial=="050070F"
replace  j12yst_5=.  if serial=="050070F"
replace  j12mfi_5=.  if serial=="050070F"
replace  j12yfi_5=.  if serial=="050070F"
```

and so on.

```
*************************************************************
This deals more quirky totspells and splits tot and out into parts
*************************************************************

□
gen     uout=1 if njlun_5>0 & njlun_5~=.;
□
replace uout=0 if njlun_5==0 | njlun_5==.;
lab var uout "unemployed out dummy"                    ;

replace stayers=0 if uout==1                            ;

replace njl_5=0 if njl_5==. ;

replace nj2l=0 if njl_5~=. & nj2l==.                   ;

gen     preout=totspell-postosp if totspell~=. & postosp~=.;
replace preout=0 if totspell==0
;
g preout22=preout*preout
;
gen     ggrsswk4=N4269*365/52 if N4267==1;
replace ggrsswk4=N4269        if N4267==2;
replace ggrsswk4=N4269*26/52  if N4267==3;
```

```
replace ggrsswk4=N4269*12/52  if N4267==4;
replace ggrsswk4=N4269*4/52   if N4267==5;
replace ggrsswk4=N4269*2/52   if N4267==6;
replace ggrsswk4=N4269/52     if N4267==7;

lab var ggrsswk4 "Gross weekly cur pay wave 4";

g rw4=ggrsswk4/rpis4;
replace rw4=. if rw4<5;
replace rw4=. if rw4>10000 & rw4~=.;
g rhw4=rw4/hours4;
replace rhw4=. if hours4==99;
```

```
gen     ggrsswk5=N500543 if N500549==1;
replace ggrsswk5=N500543*26/52        if N500549==2;
replace ggrsswk5=N500543*13/52  if N500549==3;
replace ggrsswk5=N500543*12/52  if N500549==4;
replace ggrsswk5=N500543/52   if N500549==5;

lab var ggrsswk5 "Gross weekly cur pay wave 5";

g rw5=ggrsswk5/rpi92;
replace rw5=. if rw5<5;
replace rw5=. if rw5>10000 & rw5~=.;
g rhw5=rw5/hrsc_5;

/*
g pweek5=gypayc_5/52  /* converts annual gross into weekly gross */
;
g rw5=pweek5/rpi92 /* converts weekly into real weekly jan 92 prices
*/;
g rhw5=rw5/hrsc_5 /* hourly pay */;

g rw4=rhw4*hours4 ;

lab var rw4 "real gross weekly pay wave 4 ";
*/
gen logw5=log(rhw5)                                          ;
label var logw5 "Log hourly real wage wave5"    ;

/* drop outliers */
drop if rhw5>200 & rhw5~=.;
drop if totspell>20 & totspell~=.;

gen exp2=totspell*totspell
;
lab var exp2 "Experience squared"                              ;

gen preout2=preoutsp*preoutsp                                  ;
lab var preout2 "Preout squared"                               ;

gen postosp2=postosp*postosp
;
lab var postosp2 "Postout squared"
;

/* sort out odd totspells on case by case inspection*/

replace totspell=j2spell+j3spell if totspell==0 & j1spell==. &
j2spell~=.&j3spell~=.;
```

```
replace totspell1=j2spell1+j3spell1+j4spell1 if totspell1==0 & j1spell1==. &
j2spell1~=.&j3spell1~=.&j4spell1~=.;
replace totspell1=j4spell1+j5spell1+j6spell1 if totspell1==0 & j1spell1==. &
j6spell1~=.&j5spell1~=.&j4spell1~=.;
replace totspell1=j1spell1+j2spell1+j3spell1+j4spell1+j5spell1+j6spell1
+j7spell1+j8spell1+j9spell1+j10spell1+j11spell1+j12spell1
if totspell1==0 & jnall_5>12 & jnall_5~=.
 & j2spell1~=.&j3spell1~=.&j4spell1~=. & j1spell1~=.&j5spell1~=.&j6spell1~=.
  & j7spell1~=.&j8spell1~=.&j9spell1~=.
   & j10spell1~=.&j11spell1~=.&j12spell1~=.;
replace totspell1=j1spell1+j2spell1+j3spell1+j4spell1+j5spell1+j6spell1
+j7spell1+j8spell1+j9spell1+j10spell1+j11spell1+j12spell1
if totspell1==0 & jnall_5==.
& j2spell1~=.&j3spell1~=.&j4spell1~=. & j1spell1~=.&j5spell1~=.&j6spell1~=.
  & j7spell1~=.&j8spell1~=.&j9spell1~=.
   & j10spell1~=.&j11spell1~=.&j12spell1~=.;
replace totspell1=j2spell1+j3spell1+j4spell1+j5spell1+j6spell1
+j7spell1+j8spell1+j9spell1
if totspell1==0 & j1spell1==.
& j2spell1~=.&j3spell1~=.&j4spell1~=. &j5spell1~=.&j6spell1~=.
  & j7spell1~=.&j8spell1~=.&j9spell1~=.;
replace totspell1=j1spell1+j2spell1+j3spell1+j4spell1+j5spell1+j6spell1
+j7spell1+j8spell1+j9spell1
if totspell1==0 & j1spell1~=.
& j2spell1~=.&j3spell1~=.&j4spell1~=. &j5spell1~=.&j6spell1~=.
  & j7spell1~=.&j8spell1~=.&j9spell1~=. & jnall_5==.;
replace totspell1=j1spell1+j2spell1+j3spell1+j4spell1+j5spell1+j6spell1
+j7spell1
if totspell1==0 & j1spell1~=.
& j2spell1~=.&j3spell1~=.&j4spell1~=. &j5spell1~=.&j6spell1~=.
 & jnall_5==8 & j7spell1==.;
replace totspell1=j2spell1+j3spell1+j4spell1+j5spell1+j6spell1
+j7spell1+j8spell1
if totspell1==0 & j1spell1==.
& j2spell1~=.&j3spell1~=.&j4spell1~=. &j5spell1~=.&j6spell1~=.
  & j7spell1~=.&j8spell1~=.;
replace totspell1=j2spell1+j3spell1+j1spell1 if totspell1==0 & j4spell1==.
& j2spell1~=.&j3spell1~=.&j1spell1~=.;
replace totspell1=j1spell1+j2spell1 if totspell1==0 & j3spell1==.
& j1spell1~=.&j2spell1~=.;
replace totspell1=j5spell1 if totspell1==0 & j1spell1==.
& j5spell1~=.;
replace totspell1=j2spell1+j3spell1+j4spell1+j5spell1+j6spell1 if
totspell1==0 & j1spell1==.
& j2spell1~=.&j3spell1~=.&j4spell1~=.& j5spell1~=.&j6spell1~=.;
replace totspell1=j1spell1+j2spell1+j3spell1+j4spell1+j5spell1 if
totspell1==0 & j1spell1~=.
& j2spell1~=.&j3spell1~=.&j4spell1~=.& j5spell1~=.&j6spell1==.;
replace totspell1=j1spell1+j2spell1+j3spell1+j4spell1+j5spell1+j6spell1 if
totspell1==0 & jnall_5==12
& j1spell1~=.&j2spell1~=.&j3spell1~=.& j4spell1~=.&j5spell1~=.&j6spell1~=.;
replace totspell1=j2spell1+j3spell1+j4spell1+j5spell1 if totspell1==0 &
j1spell1==.
& j2spell1~=.&j3spell1~=.& j4spell1~=.&j5spell1~=.;
replace totspell1=j2spell1 if totspell1==0 & j1spell1==. & j2spell1~=.;
replace totspell1=j1spell1 if totspell1==0 & j2spell1==.& j1spell1~=.;
replace totspell1=j1spell1+j2spell1+j3spell1+j4spell1+j5spell1 if
totspell1==0 & j6spell1==.
& j1spell1~=.&j2spell1~=.&j3spell1~=.& j4spell1~=.&j5spell1~=.;
replace totspell1=j1spell1+j2spell1+j3spell1+j4spell1 if totspell1==0 &
j5spell1==.
```

```
& j2spell~=.&j3spell~=.&j4spell~=.&j1spell~=.;
replace totspell=j1spell+j2spell+j3spell+j4spell+j5spell+j6spell
+j7spell+j8spell+j9spell+j10spell
if totspell==0 & j11spell==.
& j1spell~=.& j2spell~=.&j3spell~=.&j4spell~=. &j5spell~=.&j6spell~=.
  & j7spell~=.&j8spell~=.&j9spell~=.& j10spell~=.;
replace totspell=j1spell+j3spell+j4spell+j5spell+j6spell+j7spell if
serial=="986137J";
replace totspell=j1spell+j2spell+j3spell+j4spell+j6spell if
serial=="350057N";
replace
totspell=j2spell+j3spell+j4spell+j5spell+j6spell+j7spell+j8spell+j9spe
ll
+j10spell+j11spell if serial=="380064D";
replace totspell=j2spell+j4spell+j5spell if serial=="513128Q";
replace totspell=j2spell+j4spell+j5spell if serial=="513129S";
replace totspell=j1spell+j3spell+j4spell+j5spell+j6spell+j7spell
if serial=="986138L";
replace totspell=j2spell+j3spell+j4spell+j5spell+j6spell+j7spell
if serial=="X37001U";
replace
totspell=j1spell+j2spell+j3spell+j5spell+j6spell+j7spell+j8spell+j9spe
ll
+j10spell+j11spell+j12spell if serial=="X80110U";
replace totspell=j1spell+j4spell+j5spell
if serial=="Y00337F";
replace totspell=j1spell+j4spell+j5spell
if serial=="Y00339L";
replace totspell=j2spell+j3spell+j4spell+j5spell+j6spell
if serial=="Y01583C";
replace totspell=j1spell+j5spell+j6spell+j7spell+j8spell+j9spell
+j10spell+j11spell+j12spell if serial=="Y30233N";
replace totspell=j2spell+j3spell+j4spell+j5spell+j6spell+j7spell
+j8spell+j9spell+j12spell if serial=="010145L";
replace totspell=j1spell+j2spell+j3spell+j5spell
if serial=="282114V";
replace totspell=j2spell+j4spell
if serial=="650086T";
replace totspell=j1spell+j2spell+j3spell+j4spell+j5spell
if serial=="850031F";


/* fix up out spells  replace start month with interview month if
missing (random month assignment)*/

log using fixup.log, replace ;
replace nj1mst=intmth_5 if nj1mst==0;
replace nj2mst=intmth_5 if nj2mst==0;
replace nj3mst=intmth_5 if nj3mst==0;
replace nj4mst=intmth_5 if nj4mst==0;
replace nj5mst=intmth_5 if nj5mst==0;
replace nj6mst=intmth_5 if nj6mst==0;
replace nj7mst=intmth_5 if nj7mst==0;
replace nj8mst=intmth_5 if nj8mst==0;
replace nj9mst=intmth_5 if nj9mst==0;
replace nj10mst=intmth_5 if nj10mst==0;
replace nj11mst=intmth_5 if nj11mst==0;
replace nj12mst=intmth_5 if nj12mst==0;

replace nj1mfi=intmth_5 if nj1mfi==0;
replace nj2mfi=intmth_5 if nj2mfi==0;
```

```
replace nj3mfi=intmth_5 if nj3mfi==0;
replace nj4mfi=intmth_5 if nj4mfi==0;
replace nj5mfi=intmth_5 if nj5mfi==0;
replace nj6mfi=intmth_5 if nj6mfi==0;
replace nj7mfi=intmth_5 if nj7mfi==0;
replace nj8mfi=intmth_5 if nj8mfi==0;
replace nj9mfi=intmth_5 if nj9mfi==0;
replace nj10mfi=intmth_5 if nj10mfi==0;
replace nj11mfi=intmth_5 if nj11mfi==0;
replace nj12mfi=intmth_5 if nj12mfi==0;

replace nj1yst=91 if nj1yst==0;
replace nj2yst=91 if nj2yst==0;
replace nj3yst=91 if nj3yst==0;
replace nj4yst=91 if nj4yst==0;
replace nj5yst=91 if nj5yst==0;
replace nj6yst=91 if nj6yst==0;
replace nj7yst=91 if nj7yst==0;
replace nj8yst=91 if nj8yst==0;
replace nj9yst=91 if nj9yst==0;
replace nj10yst=91 if nj10yst==0;
replace nj11yst=91 if nj11yst==0;
replace nj12yst=91 if nj12yst==0;

replace nj1yfi=91 if nj1yfi==0;
replace nj2yfi=91 if nj2yfi==0;
replace nj3yfi=91 if nj3yfi==0;
replace nj4yfi=91 if nj4yfi==0;
replace nj5yfi=91 if nj5yfi==0;
replace nj6yfi=91 if nj6yfi==0;
replace nj7yfi=91 if nj7yfi==0;
replace nj8yfi=91 if nj8yfi==0;
replace nj9yfi=91 if nj9yfi==0;
replace nj10yfi=91 if nj10yfi==0;
replace nj11yfi=91 if nj11yfi==0;
replace nj12yfi=91 if nj12yfi==0;

replace      nj12spel=(nj12yfi_+nj12mfi_/12)-(nj12yst_+nj12mst_/12) if
nj12yst_~=.
& nj12yfi_~=.  & nj12spel==.& nj12int~=. & nj12int>0;

replace      nj11spel=(nj11yfi_+nj11mfi_/12)-(nj11yst_+nj11mst_/12) if
nj11yst_~=.
& nj11yfi_~=. & nj11spel==.& nj11int~=. & nj11int>0;

replace      nj10spel=(nj10yfi_+nj10mfi_/12)-(nj10yst_+nj10mst_/12) if
nj10yst_~=.
& nj10yfi_~=. & nj10spel==.& nj10int~=. & nj10int>0;

replace      nj9spell=(nj9yfi_5+nj9mfi_5/12)-(nj9yst_5+nj9mst_5/12) if
nj9yst_5~=.
& nj9yfi_5~=. & nj9spell==.& nj9int~=. & nj9int>0;

replace      nj8spell=(nj8yfi_5+nj8mfi_5/12)-(nj8yst_5+nj8mst_5/12) if
nj8yst_5~=.
& nj8yfi_5~=. & nj8spell==.& nj8int~=. & nj8int>0;

replace      nj7spell=(nj7yfi_5+nj7mfi_5/12)-(nj7yst_5+nj7mst_5/12) if
nj7yst_5~=.
& nj7yfi_5~=. & nj7spell==.& nj7int~=. & nj7int>0;
```

```
replace      nj6spell=(nj6yfi_5+nj6mfi_5/12)-(nj6yst_5+nj6mst_5/12) if
nj6yst_5~=.
& nj6yfi_5~=. & nj6spell==.& nj6int~=. & nj6int>0;

replace      nj5spell=(nj5yfi_5+nj5mfi_5/12)-(nj5yst_5+nj5mst_5/12) if
nj5yst_5~=.
& nj5yfi_5~=. & nj5spell==.& nj5int~=. & nj5int>0;

replace      nj4spell=(nj4yfi_5+nj4mfi_5/12)-(nj4yst_5+nj4mst_5/12) if
nj4yst_5~=.
& nj4yfi_5~=. & nj4spell==.& nj4int~=. & nj4int>0;

replace      nj3spell=(nj3yfi_5+nj3mfi_5/12)-(nj3yst_5+nj3mst_5/12) if
nj3yst_5~=.
& nj3yfi_5~=. & nj3spell==.& nj3int~=. & nj3int>0;

replace      nj2spell=(nj2yfi_5+nj2mfi_5/12)-(nj2yst_5+nj2mst_5/12) if
nj2yst_5~=.
& nj2yfi_5~=. & nj2spell==.& nj2int~=. & nj2int>0;

replace     nj1spell=(nj1yfi_5+nj1mfi_5/12)-(nj1yst_5+nj1mst_5/12) if
nj1yst_5~=.
& nj1yfi_5~=. & nj1spell==. & nj1int~=. & nj1int>0;
log close;

/* fix up outliers */
replace njno_5=2 if serial=="Y30202A";
replace nj1spell=(nj1yfi_5+nj1mfi_5/12)-(nj1yst_5+nj1mst_5/12) if
serial=="Y30202A";
replace nj2spell=(nj2yfi_5+nj2mfi_5/12)-(nj2yst_5+nj2mst_5/12) if
serial=="Y30202A";
replace nj1_5=nj2spell if serial=="Y30202A";

replace nj1spell=0.083 if serial=="Y00290F";
replace nj2spell=0.083 if serial=="093239P";
replace nj1spell=0.166 if serial=="550141R";
replace nj2spell=0.083 if serial=="093240X";
replace nj2spell=0.083 if serial=="425038Y";

replace njno_5=6 if serial=="092121J";
replace nj1spell=(nj1yfi_5+nj1mfi_5/12)-(nj1yst_5+nj1mst_5/12) if
serial=="Y01010B";
replace nj1_5=nj1spell if serial=="Y01010B";

replace njno_5=1 if serial=="610026X";
replace nj1spell=(nj1yfi_5+nj1mfi_5/12)-(nj1yst_5+nj1mst_5/12) if
serial=="610026X";
replace nj1_5=nj1spell if serial=="610026X";

g outspell=0 if nj1spell==.;
replace outspell=nj1spell+nj2spell+nj3spell+nj4spell+nj5spell+nj6spell
+nj7spell+nj8spell+nj9spell+nj10spel+nj11spel+nj12spel if njno_5==12;
replace outspell=nj1spell+nj2spell+nj3spell+nj4spell+nj5spell+nj6spell
+nj7spell+nj8spell+nj9spell+nj10spel+nj11spel          if njno_5==11;
replace outspell=nj1spell+nj2spell+nj3spell+nj4spell+nj5spell+nj6spell
+nj7spell+nj8spell+nj9spell+nj10spel                   if njno_5==10;
replace outspell=nj1spell+nj2spell+nj3spell+nj4spell+nj5spell+nj6spell
+nj7spell+nj8spell+nj9spell                            if njno_5==9;
replace outspell=nj1spell+nj2spell+nj3spell+nj4spell+nj5spell+nj6spell
+nj7spell+nj8spell                                     if njno_5==8;
replace outspell=nj1spell+nj2spell+nj3spell+nj4spell+nj5spell+nj6spell
```

```
+nj7spell                                    if njno_5==7;
replace outspell=nj1spell+nj2spell+nj3spell+nj4spell+nj5spell+nj6spell
                        if njno_5==6;
replace outspell=nj1spell+nj2spell+nj3spell+nj4spell+nj5spell
                        if njno_5==5;
replace outspell=nj1spell+nj2spell+nj3spell+nj4spell
                        if njno_5==4;
replace outspell=nj1spell+nj2spell+nj3spell
                        if njno_5==3;
replace outspell=nj1spell+nj2spell if njno_5==2;
replace outspell=nj1spell if njno_5==1;

/* fix up those with incomplete njspell info */

replace outspell=nj1spell+nj2spell+nj3spell+nj4spell if njno_5==.
& nj1spell~=.&nj2spell~=.&nj3spell~=.&nj4spell~=. &outspell==.;

replace outspell=nj6spell+nj5spell+nj2spell+nj3spell+nj4spell if
njno_5==6
&nj6spell~=.& nj5spell~=.&nj2spell~=.&nj3spell~=.&nj4spell~=. &
nj1spell==.& outspell==.;

replace outspell=nj6spell+nj5spell+nj2spell+nj3spell+nj4spell
+nj7spell+nj8spell+nj9spell+nj10spel
if njno_5==10
&nj6spell~=.& nj5spell~=.&nj2spell~=.&nj3spell~=.&nj4spell~=. &
&nj7spell~=.& nj8spell~=.&nj9spell~=.&nj10spel~=.&
nj1spell==.& outspell==.;

replace outspell=nj6spell+nj5spell+nj2spell+nj3spell+nj4spell
+nj7spell+nj8spell+nj9spell+nj10spel+nj11spel+nj12spel
if njno_5==12
&nj6spell~=.& nj5spell~=.&nj2spell~=.&nj3spell~=.&nj4spell~=. &
&nj7spell~=.& nj8spell~=.&nj9spell~=.&nj10spel~=.&nj11spel &
nj1spell==.& outspell==.;

replace outspell=nj1spell+nj2spell+nj3spell+nj4spell if njno_5==5
&nj1spell~=.&nj2spell~=.&nj3spell~=.&nj4spell~=. &
nj5spell==.& outspell==.;

replace outspell=nj2spell if njno_5==2
& nj1spell==.& outspell==.;

replace outspell=nj1spell+nj2spell if njno_5==3
& nj1spell==.& outspell==.;

replace outspell=nj1spell if njno_5==2
& nj2spell==.& outspell==. & serial~="500231K";

replace nj9spell=(91+(intmth_5/12))-j1fidat if serial=="683079H";
replace outspell=nj1spell+nj5spell+nj6spell+nj8spell+nj9spell if
serial=="683079H";

g out2=outspell*outspell;

/* to create actual experience by ft/pt status */

replace j4spell=.083 if -.1<=j4spell & j4spell<0;

g ftspell=0;
g ftspell1=j1spell if j1ft==1 & j1ee==1 ;
```

```
replace ftspell1=0 if ftspell1==.;
g ftspell2=j2spell1 if j2ft==1 & j2ee==1 ;
replace ftspell2=0 if ftspell2==.;
g ftspell3=j3spell1 if j3ft==1 & j3ee==1 ;
replace ftspell3=0 if ftspell3==.;
g ftspell4=j4spell1 if j4ft==1 & j4ee==1 ;
replace ftspell4=0 if ftspell4==.;
g ftspell5=j5spell1 if j5ft==1 & j5ee==1 ;
replace ftspell5=0 if ftspell5==.;
g ftspell6=j6spell1 if j6ft==1 & j6ee==1 ;
replace ftspell6=0 if ftspell6==.;
g ftspell7=j7spell1 if j7ft==1 & j7ee==1 ;
replace ftspell7=0 if ftspell7==.;
g ftspell8=j8spell1 if j8ft==1 & j8ee==1 ;
replace ftspell8=0 if ftspell8==.;
g ftspell9=j9spell1 if j9ft==1 & j9ee==1 ;
replace ftspell9=0 if ftspell9==.;
g ftspl110=j10spell1 if j10ft==1 & j10ee==1 ;
replace ftspl110=0 if ftspl110==.;
g ftspl111=j11spell1 if j11ft==1 & j11ee==1 ;
replace ftspl111=0 if ftspl111==.;
g ftspl112=j12spell1 if j12ft==1 & j12ee==1 ;
replace ftspl112=0 if ftspl112==.;

replace ftspell1=ftspell11+ftspell12+ftspell13+ftspell14+ftspell15+ftspell16
+ftspell17+ftspell18+ftspell19+ftspl110+ftspl111+ftspl112;
replace ftspell1=ftspell13+ftspell14+ftspell15+ftspell16
+ftspell17+ftspell18+ftspell19+ftspl110+ftspl111
 if serial=="380064D";
replace ftspell1=ftspell12+ftspell14
 if serial=="513128Q";
replace ftspell1=ftspell12+ftspell14
 if serial=="513129S";
replace ftspell1=ftspell13+ftspell14+ftspell15+ftspell16
+ftspell17
 if serial=="986138L";
replace ftspell1=ftspell12+ftspell13+ftspell14+ftspell15+ftspell16
 if serial=="X37001U";
replace ftspell1=ftspell11+ftspell12+ftspell13+ftspell15+ftspell16
+ftspell17+ftspell18+ftspell19+ftspl110+ftspl111+ftspl112
 if serial=="X80110U";
replace ftspell1=ftspell14+ftspell15
 if serial=="Y00337F";
replace ftspell1=ftspell11+ftspell14+ftspell15
 if serial=="Y00339L";
replace ftspell1=ftspell12+ftspell13+ftspell14+ftspell15+ftspell16
 if serial=="Y01583C";
replace ftspell1=ftspell11+ftspell15+ftspell17+ftspell18+ftspell19+ftspl110
 if serial=="Y30233N";
replace
ftspell1=ftspell12+ftspell13+ftspell14+ftspell15+ftspell16+ftspell17+ftspell18
+ftspell19
 if serial=="010145L";

replace ftspell1=totspell1 if ftspell1>totspell1 & ftspell1~=. &
totspell1~=.;

/* now define part-time work exp */
/*
g ptspell1=0;
g ptspell11=j1spell1 if j1ft==0 & j1ee==1 ;
```

```
replace ptspell1=0 if ptspell1==.;
g ptspell2=j2spell1 if j2ft==0 & j2ee==1 ;
replace ptspell2=0 if ptspell2==.;
g ptspell3=j3spell1 if j3ft==0 & j3ee==1 ;
replace ptspell3=0 if ptspell3==.;
g ptspell4=j4spell1 if j4ft==0 & j4ee==1 ;
replace ptspell4=0 if ptspell4==.;
g ptspell5=j5spell1 if j5ft==0 & j5ee==1 ;
replace ptspell5=0 if ptspell5==.;
g ptspell6=j6spell1 if j6ft==0 & j6ee==1 ;
replace ptspell6=0 if ptspell6==.;
g ptspell7=j7spell1 if j7ft==0 & j7ee==1 ;
replace ptspell7=0 if ptspell7==.;
g ptspell8=j8spell1 if j8ft==0 & j8ee==1 ;
replace ptspell8=0 if ptspell8==.;
g ptspell9=j9spell1 if j9ft==0 & j9ee==1 ;
replace ptspell9=0 if ptspell9==.;
g ptspll10=j10spell1 if j10ft==0 & j10ee==1 ;
replace ptspll10=0 if ptspll10==.;
g ptspll11=j11spell1 if j11ft==0 & j11ee==1 ;
replace ptspll11=0 if ptspll11==.;
g ptspll12=j12spell1 if j12ft==0 & j12ee==1 ;
replace ptspll12=0 if ptspll12==.;

replace ptspell1=ptspell11+ptspell12+ptspell13+ptspell14+ptspell15+ptspell16
+ptspell17+ptspell18+ptspell19+ptspll10+ptspll11+ptspll12;
*/
g ptspell1=totspell1-ftspell1   ;
replace ptspell1=0 if ptspell1<0;


/* now flag for all out spells */

g n1un=nj1int==1;
g n1ch=nj1int==4;
g n1ed=nj1int==3;
g n1ot=(nj1int==0 | nj1int==2 ) ;

g n2un=nj2int==1;
g n2ch=nj2int==4;
g n2ed=nj2int==3;
g n2ot=(nj2int==0 | nj2int==2) ;

g n3un=nj3int==1;
g n3ch=nj3int==4;
g n3ed=nj3int==3;
g n3ot=(nj3int==0 | nj3int==2) ;

g n4un=nj4int==1;
g n4ch=nj4int==4;
g n4ed=nj4int==3;
g n4ot=nj4int==0 | nj4int==2;

g n5un=nj5int==1;
g n5ch=nj5int==4;
g n5ed=nj5int==3;
g n5ot=nj5int==0 | nj5int==2;

g n6un=nj6int==1;
g n6ch=nj6int==4;
g n6ed=nj6int==3;
```

```
g n6ot=nj6int==0 | nj6int==2;

g n7un=nj7int==1;
g n7ch=nj7int==4;
g n7ed=nj7int==3;
g n7ot=nj7int==0 | nj7int==2;

g n8un=nj8int==1;
g n8ch=nj8int==4;
g n8ed=nj8int==3;
g n8ot=nj8int==0 | nj8int==2;

g n9un=nj9int==1;
g n9ch=nj9int==4;
g n9ed=nj9int==3;
g n9ot=nj9int==0 | nj9int==2;

g n10un=nj10int==1;
g n10ch=nj10int==4;
g n10ed=nj10int==3;
g n10ot=nj10int==0 | nj10int==2;

g n11un=nj11int==1;
g n11ch=nj11int==4;
g n11ed=nj11int==3;
g n11ot=nj11int==0 | nj11int==2;

g n12un=nj12int==1;
g n12ch=nj12int==4;
g n12ed=nj12int==3;
g n12ot=nj12int==0 | nj12int==2;

/* total unemp experience */
g nuspell=0;
g nuspell1=nj1spell if n1un==1 ;
replace nuspell1=0 if nuspell1==.;
g nuspell2=nj2spell if n2un==1  ;
replace nuspell2=0 if nuspell2==.;
g nuspell3=nj3spell if n3un==1  ;
replace nuspell3=0 if nuspell3==.;
g nuspell4=nj4spell if n4un==1  ;
replace nuspell4=0 if nuspell4==.;
g nuspell5=nj5spell if n5un==1  ;
replace nuspell5=0 if nuspell5==.;
g nuspell6=nj6spell if n6un==1  ;
replace nuspell6=0 if nuspell6==.;
g nuspell7=nj7spell if n7un==1  ;
replace nuspell7=0 if nuspell7==.;
g nuspell8=nj8spell if n8un==1  ;
replace nuspell8=0 if nuspell8==.;
g nuspell9=nj9spell if n9un==1  ;
replace nuspell9=0 if nuspell9==.;
g nuspl110=nj10spel if n10un==1  ;
replace nuspl110=0 if nuspl110==.;
g nuspl111=nj11spel if n11un==1  ;
replace nuspl111=0 if nuspl111==.;
g nuspl112=nj12spel if n12un==1  ;
replace nuspl112=0 if nuspl112==.;

replace nuspell=nuspell1+nuspell2+nuspell3+nuspell4+nuspell5+nuspell6
+nuspell7+nuspell8+nuspell9+nuspl110+nuspl111+nuspl112;
```

```
/* total child experience */
g ncspell=0;
g ncspell1=nj1spell if n1ch==1 ;
replace ncspell1=0 if ncspell1==.;
g ncspell2=nj2spell if n2ch==1  ;
replace ncspell2=0 if ncspell2==.;
g ncspell3=nj3spell if n3ch==1  ;
replace ncspell3=0 if ncspell3==.;
g ncspell4=nj4spell if n4ch==1  ;
replace ncspell4=0 if ncspell4==.;
g ncspell5=nj5spell if n5ch==1  ;
replace ncspell5=0 if ncspell5==.;
g ncspell6=nj6spell if n6ch==1  ;
replace ncspell6=0 if ncspell6==.;
g ncspell7=nj7spell if n7ch==1  ;
replace ncspell7=0 if ncspell7==.;
g ncspell8=nj8spell if n8ch==1  ;
replace ncspell8=0 if ncspell8==.;
g ncspell9=nj9spell if n9ch==1  ;
replace ncspell9=0 if ncspell9==.;
g ncspl110=nj10spel if n10ch==1  ;
replace ncspl110=0 if ncspl110==.;
g ncspl111=nj11spel if n11ch==1  ;
replace ncspl111=0 if ncspl111==.;
g ncspl112=nj12spel if n12ch==1  ;
replace ncspl112=0 if ncspl112==.;

replace ncspell=ncspell1+ncspell2+ncspell3+ncspell4+ncspell5+ncspell6
+ncspell7+ncspell8+ncspell9+ncspl110+ncspl111+ncspl112;
g ncs2=ncspell^2;

/* total ed experience */
g nespell=0;
g nespell1=nj1spell if n1ed==1 ;
replace nespell1=0 if nespell1==.;
g nespell2=nj2spell if n2ed==1  ;
replace nespell2=0 if nespell2==.;
g nespell3=nj3spell if n3ed==1  ;
replace nespell3=0 if nespell3==.;
g nespell4=nj4spell if n4ed==1  ;
replace nespell4=0 if nespell4==.;
g nespell5=nj5spell if n5ed==1  ;
replace nespell5=0 if nespell5==.;
g nespell6=nj6spell if n6ed==1  ;
replace nespell6=0 if nespell6==.;
g nespell7=nj7spell if n7ed==1  ;
replace nespell7=0 if nespell7==.;
g nespell8=nj8spell if n8ed==1  ;
replace nespell8=0 if nespell8==.;
g nespell9=nj9spell if n9ed==1  ;
replace nespell9=0 if nespell9==.;
g nespl110=nj10spel if n10ed==1  ;
replace nespl110=0 if nespl110==.;
g nespl111=nj11spel if n11ed==1  ;
replace nespl111=0 if nespl111==.;
g nespl112=nj12spel if n12ed==1  ;
replace nespl112=0 if nespl112==.;

replace nespell=nespell1+nespell2+nespell3+nespell4+nespell5+nespell6
```

```
+nespell7+nespell8+nespell9+nespl110+nespl111+nespl112;

/* total other experience */

g nospell1=nj1spell if n1ot==1 ;
replace nospell1=0 if nospell1==.;
g nospell2=nj2spell if n2ot==1  ;
replace nospell2=0 if nospell2==.;
g nospell3=nj3spell if n3ot==1  ;
replace nospell3=0 if nospell3==.;
g nospell4=nj4spell if n4ot==1  ;
replace nospell4=0 if nospell4==.;
g nospell5=nj5spell if n5ot==1  ;
replace nospell5=0 if nospell5==.;
g nospell6=nj6spell if n6ot==1  ;
replace nospell6=0 if nospell6==.;
g nospell7=nj7spell if n7ot==1  ;
replace nospell7=0 if nospell7==.;
g nospell8=nj8spell if n8ot==1  ;
replace nospell8=0 if nospell8==.;
g nospell9=nj9spell if n9ot==1  ;
replace nospell9=0 if nospell9==.;
g nospl110=nj10spel if n10ot==1  ;
replace nospl110=0 if nospl110==.;
g nospl111=nj11spel if n11ot==1  ;
replace nospl111=0 if nospl111==.;
g nospl112=nj12spel if n12ot==1  ;
replace nospl112=0 if nospl112==.;

/* other out experience */
g nospell=outspell-nespell-ncspell-nuspell;

drop if totspell>20 & totspell~=.;
drop if outspell>20 & outspell~=.;

g neverout=outspell==0 ;
g neverin=totspell==0 ;

g n1fdat=(nj1yfi_5 +(nj1mfi_5/12) ) ;
g n2sdat=(nj2yst_5 +(nj2mst_5/12) ) ;
g n2fdat=(nj2yfi_5 +(nj2mfi_5/12) ) ;
g n3sdat=(nj3yst_5 +(nj3mst_5/12) ) ;

g oneout=nj1spell~=0 & ((nj1spell~=. & nj2spell==.) | (n2sdat==n1fdat
& nj2spell~=0 & n2sdat~=.));
g twoout=nj1spell~=0 & nj1spell~=. & nj2spell~=0 & nj2spell~=. &
n2sdat~=n1fdat;
g throut=nj1spell~=0 & nj1spell~=. & nj2spell~=0 & nj2spell~=. &
nj3spell~=0 & nj3spell~=.
& n2sdat~=n1fdat & n3sdat~=n1fdat & n2sdat~=.;

/* aligns preoutsp for all those with non zero post and pre */
replace preoutsp=totsp-postosp if (preoutsp+postosp<totspell)
& (preoutsp>0 & postosp>0 & totspell~=. & totspell~=0);
replace postosp=(91+(intmth_5/12))-njlfidat if postosp==0 & totspell>0
& totspell~=.;
replace postosp=totspell if postosp>totspell & postosp~=. &
totspell~=. & totspell>0;
```

```
replace preoutsp=totspell-postosp if preoutsp==0 & totspell>0 &
totspell~=. & njno>0 & njno~=.;

replace preoutsp=totspell if durtype==1; /* continuous pre=totspell */
replace postosp=0 if durtype==1;
replace postosp2=0 if durtype==1;

replace preoutsp=totspell-postosp if serial=="287035B";

replace outspell=(91+(intmth_5/12))-jlfidat if outspell==0 & 5<=lfstc
& lfstc<99;

/* now try for post ft and post pt */
g postft=ftspell1+ftspell2+ftspell3+ftspell4+ftspell5+ftspell6
+ftspell7+ftspell8+ftspell9+ftspl110+ftspl111+ftspl112
if j1ft==1 & j1ee==1 & j1st_5>=njlfidat & j1st~=.;
replace postft=ftspell2+ftspell3+ftspell4+ftspell5+ftspell6
+ftspell7+ftspell8+ftspell9+ftspl110+ftspl111+ftspl112
if j2ft==1 & j2ee==1 & j2st_5>=njlfidat & j2st_5~=. & postft==.;
replace postft=ftspell3+ftspell4+ftspell5+ftspell6
+ftspell7+ftspell8+ftspell9+ftspl110+ftspl111+ftspl112
if j3ft==1 & j3ee==1 & j3st_5>=njlfidat & j3st~=.  & postft==.;
replace postft=ftspell4+ftspell5+ftspell6
+ftspell7+ftspell8+ftspell9+ftspl110+ftspl111+ftspl112
if j4ft==1 & j4ee==1 & j4st_5>=njlfidat & j4st~=.  & postft==.;
replace postft=ftspell5+ftspell6
+ftspell7+ftspell8+ftspell9+ftspl110+ftspl111+ftspl112
if j5ft==1 & j5ee==1 & j5st_5>=njlfidat & j5st~=. & postft==.;
replace postft=ftspell6
+ftspell7+ftspell8+ftspell9+ftspl110+ftspl111+ftspl112
if j6ft==1 & j6ee==1 & j6st_5>=njlfidat & j6st~=. & postft==.;
replace postft=ftspell7+ftspell8+ftspell9+ftspl110+ftspl111+ftspl112
if j7ft==1 & j7ee==1 & j7st_5>=njlfidat & j7st~=. & postft==.;
replace postft=ftspell8+ftspell9+ftspl110+ftspl111+ftspl112
if j8ft==1 & j8ee==1 & j8st_5>=njlfidat & j8st~=. & postft==.;
replace postft=ftspell9+ftspl110+ftspl111+ftspl112
if j9ft==1 & j9ee==1 & j9st_5>=njlfidat & j9st~=. & postft==.;
replace postft=ftspl110+ftspl111+ftspl112
if j10ft==1 & j10ee==1 & j10st_5>=njlfidat & j10st~=. & postft==.;
replace postft=ftspl111+ftspl112
if j11ft==1 & j11ee==1 & j11st_5>=njlfidat & j11st~=. & postft==.;
replace postft=ftspl112
if j12ft==1 & j12ee==1 & j12st_5>=njlfidat & j12st~=. & postft==.;

replace postft=ftspell2+ftspell3+ftspell4 if serial=="287035B";

replace postft=0 if outspell==0 | neverout==1;
replace postft=0 if postft==. & ftspell~=.;
replace postft=. if totspell==0;

g postpt=postosp-postft;
replace postpt=0 if postosp<=0;
replace postpt=0.083 if -0.1<postpt & postpt<0;
replace postpt=00 if ptspell==0;
g preft=ftspell-postft;
replace preft=0 if ftspell==0;
g prept=ptspell-postpt;

replace prept=0 if ptspell==0;
replace prept=0 if prept<0;
```

Chapter 4

Literature Review of the Theories of Human Capital and Labour Supply

4.1 Introduction

The fact that women have been more likely to interrupt their work careers than men is well known (see, for example, Becker (1965) or Mincer (1974)). The reasons why this has come to pass has largely been ascribed to the various physiological and biological characteristics of women associated with the birth and rearing of children and to arguments centred upon the sexual division of labour. However, following the increase in female labour market participation after the Second World War, especially in part-time working (see Hakim (1993), and Chapter 2), it has become far more usual to witness continuous female employment throughout the childrearing years. Some women, however, do continue to have breaks in employment and some women have longer periods out of work than others. It is interesting, therefore, to investigate whether the time spent out of work or the length of time spent out of work affects subsequent earnings. This Chapter discusses the main theoretical and empirical work relating to this thesis. The first section deals with the evolution of human capital theory and earnings determination, Section 4.3 deals with the interaction of human capital theory and labour supply, while Section 4.4 looks at the literature that deals explicitly with the effects of intermittent participation in work and subsequent effects on earnings. Section 4.5 concludes by setting the scene for our own analysis in subsequent Chapters.

4.2 Theory of Human Capital and Lifetime Earnings

There have been many varied statements about the workings of the labour market proffered by non-economists. Typically, such explanations as to why and how women interrupt their work careers are focused upon the separation of women into two distinct groups. Women are seen to enter the labour market at relatively low wages and are then witnessed to either participate continuously (whereby wage growth is positive and significant), or to work for a few years and then to withdraw for a period of time after the birth of the first child. Usually, the non-economist (see the review in Folbre (1994), for example) would label the

former group as career-minded, male-like workers, whilst the latter are seen to form the group of women returners. The career-minded female minimises the amount of labour market withdrawal following a change in family status, whilst the intermittent worker will be out of the labour market for several years. On the return to the labour market, the intermittent female is far more likely to be employed on a part-time basis than before her interruption.

To the non-economist, the splitting of women into two groups enables a logical explanation to be given as to why some female workers command high salaries whilst others are sucked into the poverty trap. This categorisation also offers an explanation as to how some labour market re-entrants are destined for a lifetime of part-time participation and low relative wages (see the evidence in Chapter 2). It is commonly thought that low re-entry wages are influenced by a number of factors. First, wages tend to increase with work experience. This experience may be separated into firm specific and general experience. Women with career breaks have thereby accumulated less work experience. Second, time away from the labour market may lead to the atrophy of vital work skills, so that re-entry wages are necessarily lower. Finally, those females who anticipate career breaks may have a low propensity to engage in training whilst in work and are thereby characterised by flatter earnings-experience profiles.

An economist might explain the observable wage differences in terms of accumulated human capital or in terms of the whether participation is part- or full-time.[1] In its broadest form, human capital theory is concerned with the acquisition of skills and the subsequent rewards to that investment. Time away from the labour market might be expected to lead to a depreciation of the skills gained before the break. This could then explain the lower wages obtained by female returners compared with continuous workers. Alternatively, employers may interpret time out as a signal of less committed workers (see Spence (1974), Layard, Nickell and Jackman (1991)) and employers may therefore offer low wages in the absence of other information about a worker's productivity. However, women who expect

[1] Various economists shed doubt on the robustness of some of these conclusions. Joshi and Paci (1998) recognise that low pay associated with female part-time work is a peculiarly British phenomenon.

to take breaks in employment could be viewed as making a conscious decision to acquire less human capital before the separation, which, if true, would be associated with lower subsequent wages and less attachment to the labour force in the future. This decision could be based on factors that are observable to the economist, namely age and existing education, or it may be influenced by factors that are unobserved, such as a "taste for work." It is important to try and distinguish between the former depreciation effect and the latter, labour supply orientated, explanation of the negative wage effect of breaks and to try to take account of the unobserved heterogeneity. The focus of Chapter 5 is to unravel these competing explanations.

The study of human capital has its origins in work that can be traced back to Smith (1776) who noted that the rewards to education would compensate for the expense of the education.[2] That the monetary value of lifetime earnings should at least be equal to the cost of acquiring such earnings (in terms of the cost of education and maintenance) has long been a centrally held view. From such beginnings, Becker's (1965) model grew and gave rise to the proliferation of human capital studies present today. Indeed, work in the 1970's sought to offer estimates of the rates of return to human capital for all countries that could provide reasonable data (see Psacharopoulos (1973, 1979)). The remainder of this section serves as a brief introduction to human capital theory and suggests reasons for its widespread adoption by economists.

Expenditure by individuals falls into two distinct categories: spending on those purchases which yield immediate utility (consumption), and those which generate future income by increasing productive capacity (investment expenditure). Human capital theory focuses on a specific type of investment by workers: the investment in skills that thereby increases the productivity of an individual. Such a process of accumulation of units of human capital is carried out through education and training.

The basic methodology of the human capital approach may be illustrated by the examination of the relationship between wages and education. In a perfectly competitive

[2] This is highlighted in Sapsford and Tzannatos (1993), page 69.

market, it is assumed that additional years of education increase the productivity of a worker, so that wages may be seen to be equal to the size of the marginal revenue product, or their present value over the life cycle. The amount of human capital accumulated varies between individuals and, assuming initially that workers are homogeneous with respect to age, sex, and race, the differences in earnings will reflect the various amounts of human capital acquired.

In the absence of uncertainty, a wealth maximising individual contemplates the benefit of additional education (in terms of increased productivity later to be rewarded in the labour market) and the cost of such education (both the direct cost of books and tuition fees and the opportunity cost of time spent not in the labour market). The incentive to engage in education is a result of the higher future income stream from the increased productive capacity which results from extra schooling. This productivity is assumed to be rewarded throughout the individual's working life.

The rational individual with perfect information will calculate the return from the investment expenditure on education in a manner analogous to the entrepreneur who computes the return to physical capital. That is, the individual considers the net present value of the earnings gain from additional, non-compulsory schooling that lasts p periods as

$$\sum_{t=1}^{T-p} \frac{E_p - E_{p0}}{(1+i)^t} \qquad (4.1)$$

where T-p represents the working life of the individual who has invested an extra p years in education, E_p is earnings after the investment, E_{p0} is earnings in the absence of the investment and i is the market discount rate. The present value of the gain is then compared to the cost of acquiring such education in terms of the opportunity cost of the p^{th} period,

$$E_{p0} + DC_p \qquad (4.2)$$

where DC_p are the direct costs of schooling. An individual will continue to acquire p additional years of education for as long as (4.1) is greater than (4.2).

Equivalently, the rational individual may contemplate the internal rate of return, r, on investing in the additional years of schooling and compare this with the market rate of interest, i. If the value of r which equates

$$\sum_{t=1}^{T-p} \frac{E_p - E_{p0}}{(1+r)^t} = E_{p0} + DC_p \qquad (4.3)$$

is greater than the value of i, the individual has an incentive to acquire more schooling. Thus r is the rate of return to acquiring p extra years of education.

If we simplify the above to consider an individual with an assumed infinite time horizon and a subsidised, state education system (where the direct costs of schooling are zero), then we have $\frac{E_{p0} - E_{p0}}{r} = E_{p0}$, which gives an internal rate of return of $r = \frac{E_p - E_{p0}}{E_{p0}}$, or the proportionate change in earnings resulting from the investment in education.

The algebra above provides a rationale for human capital acquisition in the form of extra years of schooling. The theory may be extended to incorporate other forms of human capital investment, such as training. It is similar to physical capital investment appraisal. Mincer (1974) developed this approach in a way that further added to its popularity and it is this extension which forms the basis of Section 4.3.

4.3 Human Capital and the Theory of Labour Supply

The theory of human capital investment can also be made to rest within the theory of dynamic labour supply. This attempts to explain the pattern of age-employment profiles observed in Chapter 2 in terms of optimising behaviour by individuals (see Section 5.5 of Killingsworth (1983) for an elaboration of this point). In the static model of labour supply, an individual's labour force participation decision depends only on current wages, prices and income. These static models assume that wages are at each point in time exogenous. Any change in wage rates then generates income and relative price (substitution) effects which affect the number of hours supplied. If wages rise then the income effect is to reduce hours supplied, and the substitution effect will always generate a rise in desired hours, as individuals move away from relatively more expensive leisure. The evidence of rising

female participation over time observed in Chapter 2 is then consistent with the dominance of the substitution effect over the income effect.

Dynamic Labour Supply

In dynamic models, individuals can use saving, or borrowing, to transfer earnings from one period to another and adjust their labour supply accordingly, knowing that a decision today will affect choices for tomorrow. Again, simple dynamic models assume that wages, prices and income are exogenous in each period. However, if wages are essentially determined as a function of the level of human capital, and this in turn depends on the amounts of time spent investing in the acquisition of human capital, then wages, the decision to enter work and the amount of investment in human capital are all endogenously determined.

Killingsworth (1983) notes that there are several versions of the human capital model of dynamic labour supply. In one version, used by Blinder and Weiss (1976), individuals divide their time between work and leisure and choose between jobs providing different opportunities for training. So individuals invest in different amounts of human capital by deciding on which type of job to take. The stock of human capital at any point is

$$K(t) = K(t-1) + k(t) - \delta K(t-1) \qquad (4.4)$$

where $k(t)$ is the amount of new gross investment in human capital and δ is the rate of depreciation of the existing human capital stock in each period. The amount of human capital acquired in any time period, $k(t)$, depends on the amount of time spent at work, $H(t)$, the existing stock of human capital, $K(t)$ and the level of "training" that goes with the job, $T(t)$. Thus

$$k(t) = k\,[\,H(t), K(t), T(t)] \qquad k'_j > 0 \quad j = H, K, T \qquad (4.5)$$

Inclusion of the stock of human capital in the human capital production function means that acquiring skills is easier, the more skills an individual already possesses. Here, $T(t)$ is an index ranging from 0 (no training) to 1 (all training), so that $K(t)T(t)$ is then a measure of the amount of market productivity devoted to accumulating human capital rather than market work, and $H(t)K(t)T(t)$ is the total amount of investment in human capital in any period. Productivity is related to the stock of human capital at that point, $P(t) = \phi[K(t)]$.

Wages depend positively on productivity, but negatively on the amount of training involved in the job (assuming that the individual bears some of the costs of training), so

$$W(t) = g[F(t)]P(t) \qquad g'>0 \qquad (4.6)$$

Hence when a worker invests in human capital her current wage is lower than her actual market productivity, but there is a trade off between lower current earnings and higher future earnings through the realisation of further human capital investment.

These models proceed with an attempt to evaluate the lifetime present values of the investment in human capital and non-investment options. The general implication for age earnings profiles is that human capital investment will take place when the opportunity costs of training are low, that is, when current earnings are low when individuals are young, so that there is a long period of time to recoup the costs of any investment. The higher current productivity as a result of past investments, the higher the current wage and the greater the opportunity cost of further investment. This gives rise to the familiar n-shaped age earnings profile, with depreciation and lack of further investment in human capital explaining the downturn in the profile. However, if the rate of depreciation is large, it may be that investment in training will be spread over the life cycle. Likewise since lifetime labour supply depends on an evaluation of the in and out of work costs and benefits, then individuals will generally supply fewer hours when the opportunity costs, primarily wages, are low. Net of any offsetting discount rate effects, which may create a preference for income now and leisure later, this will generate an n-shaped age employment profile. The flatter the age earnings profile, the flatter the age employment profile.

However, as Killingsworth (1983) indicates, the estimation of endogenous wage, dynamic labour supply models has many difficulties. The principal variables of interest can sometimes not be observed and few variables in the simultaneous system are exogenous. Further, the principal data set used in Chapter 5 and Chapter 7 covers only a single age cohort and not women at each stage of the life cycle. For these reasons, we choose only to note the contribution to the literature of dynamic models and address the potential endogeneity of wages, human capital and labour supply in other ways that are highlighted in Section 4.4.

Household Labour Supply

It is also reasonable to believe that individual decisions to work are not undertaken without regard to the attitudes and labour market circumstances of other household members. Labour supply theory deals with this issue in a number of different ways. The simplest way is to assume that partner's status and earnings are exogenous, so that non-labour income can include any partner's earnings.[3] Any change in partner's earnings shifts the budget constraint up or down, generating a pure income effect on labour supply.

One alternative to this is to try to develop a family or household aggregate utility function where the objects of choice are the level of household consumption, G, and the individual amounts of leisure time, L, (see Ashenfelter and Heckman (1974)). The household is assumed to pool its total income so that household utility is then maximised subject to a family budget constraint. However, with the specification of a family utility function $U = U(G, L_1, L_2, ..., L_n)$, (where L_i is the non-market hours consumed by the ith member), there are two types of substitution effects arising from wage changes. Each adult now has an own-substitution effect (which represents that member's labour supply response to a change in their own wage). In addition, there exist cross-substitution effects, reflecting the member's labour supply response to a change in the wage rate of the other family member. The sign of these latter effects may be positive (if leisure time of household members are substitutes) or negative (if leisure times are complementary). One consequence of the family utility function is that the cross-substitution effects of a change in one adult's wage rate on the other's labour supply must be equal to any change in the latter's wage rate on the other member's labour supply. However, since the income effects may not be equal, the total effect on labour supply need not be the same.

These models again impose rather tight restrictions on the structural form. Their principal influence on this thesis, which deals mainly with reduced forms, is the recognition that household variables may affect female labour supply decisions through changes in the

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[3] Since these models are often applied to female labour supply they are sometimes termed "male chauvinist" models.

reservation wage and wage offer criteria, and, where possible, we take account of household variables in the Chapters that follow.

Time Allocation Models

Although the specification of a family utility function is an obvious improvement in the literature, the early household production models of, say, Mincer (1962) and Becker (1965), tended to emphasise the simple responses to changes in market wage rates, incomes and technologies that influenced the production function for home commodities. Becker acknowledged that virtually all commodities require a time input in their consumption, such that any consumption activity requires the summation of a market price and the value of time required to produce and or to consume it. The advent of the allocation of time models, (see Gronau (1973), (1977)), suggests that the household's supply of market hours is jointly determined with consumption activity. This thereby sees the disappearance of the straight labour-leisure trade off.

In this group of models, households maximise utility, $U= U(Z_1, Z_2, ..., Z_m)$, subject to a budget constraint. Here, the Z's represent more basic commodities than the G's above. Households produce these commodities by combining time and market goods as defined by a household production function $Z_i = Z_i(G_i, t_i)$ for $i=1, ..., m$, where G_i and t_i are goods and time inputs to this process. The household production function is often assumed to be of the fixed coefficient type, $Z_i = G_i/a_i$ and $Z_i = t_i/b_i$, where a_i and b_i are units of goods and units of time per unit of the associated activity. The models also operate under the usual time constraint

$$T = \sum_{i=1}^{m} t_i + H \qquad (4.6)$$

where H is the number of hours worked, together with a money income constraint:

$$\sum_{i=1}^{m} P_{G_i} G_i = P_L H + V \qquad (4.7).$$

If $T=H$, such that the individual is subject to the full income constraint, we have

$$\sum_{i=1}^{m} P_{G_i} G_i + P_L \sum_{i=1}^{m} t_i = P_L T + V \qquad (4.8)$$

Substituting G_i/a_i and t_i/b_i into (4.8) yields

$$\sum P_{G_i} Z_i a_i + P_L \sum Z_i b_i = \sum_{i=1}^{m} \pi_i Z_i \qquad (4.9)$$

where $\pi_i = P_{Gi}a_i + P_L b_i$ *for* $i = 1, ..., m$ and π_i represents the full cost of consuming or producing the basic commodity Z_i .

Maximising the utility function subject to the full income constraint yields

$$\frac{\partial U / \partial Z_i}{\partial U / \partial Z_j} = \frac{MU_i}{MU_j} = \frac{\pi_i}{\pi_i} \qquad (4.10)$$

for activities $i,j = 1, ..., m$.

So, within this class of models, an individual consumes or produces basic commodities i and j until the marginal rate of substitution between any two activities just equals the ratio of their full costs. Full costs here include the value of time. Women deciding whether to have children will then compare the costs and benefits of this decision with all other alternatives.

Killingsworth (1983) concludes that the most valuable contribution of this class of models is that they provide a convenient framework for analysing the division of non-market time into different components, (childrearing, leisure, housework and so on), that is ignored by standard labour supply theory. However, he believes that the determinants of labour supply, (prices, income and wages), are essentially the same as in other labour supply models and, as such, time allocation models give few new insights about labour supply behaviour. In the following Chapters, we do implicitly acknowledge the contribution of this field by dividing non-work into separate components, unemployment and economic inactivity, dividing the latter into home production, education and other categories.

Fixed Costs of Labour Supply

One potentially important impediment to the return to work for many women with children is the cost of childcare. If women enter work then they incur direct costs of childcare that would not arise if they remained at home to look after their child. This observation belongs

to the literature on fixed costs of labour supply popularised by Cogan (1981). The effect of incurring childcare costs is to shift down the budget constraint by an amount equal to the cost of childcare if and only if the individual decides to work. There is a pure (negative) income effect only if a woman works. If non-market time is a normal good, then hours worked and labour market participation will fall. The implications for labour supply are very intriguing. Since individuals will not participate unless they recoup their fixed costs, then we may expect to observe large discrete jumps in hours supplied when the hourly wage exceeds the reservation wage. There is an interesting literature on whether subsidising childcare leads to an increase in labour supply (see Connelly (1992) and Anderson and Levine (1999) for recent studies). The rise in female labour force participation observed in Chapter 2, and recent changes to the benefit system (notably, the Working Families Tax Credit) have brought the issue to the forefront of public debate. However, in the absence of information on childcare costs in our data sets, we leave this extension to future work. In the Chapters that follow, dummy variables on the presence and age of young children will capture potential childcare costs (see Nakamura and Nakamura (1992) for a summary of the effects of children on female labour supply).

4.4 Measuring the Impact of Intermittent Participation on Earnings

The unifying theme of recent work on human capital theory is the adoption of the standard Mincerian methodology. Mincer (1974) addresses the central issue of earnings inequality. First, it is assumed that earnings increase over the lifecycle at a decreasing rate and, second, that earnings rise with the amount of education undertaken. Such an approach works well for all agents whose investment in human capital is a monotonically declining function of age and who remain in work almost continuously. Card (1998) finds the rate of return of one extra year of education on hourly earnings to be around 10 per cent in the United States. This return has grown between 35 and 50 per cent since the early 1980's. However, the stylised lifetime earnings profile which is continuous with a single-peak is clearly inappropriate for groups of workers who have time out of the labour market. This may be the case where a large proportion of workers in the labour force are female.

Workers who anticipate small amounts of lifetime labour market participation due to repeated breaks may engage in less formal education and less training before and after any work break. This will produce a different (flatter), age-earnings profile from women who continuously invest in human capital. Conversely, some women, upon completion of time outside the labour market, may have strong incentives to (re-)invest in the acquisition of skills if those skills have depreciated during a spell out of work. For those who do have career breaks, earnings may take some time to regain their pre-break level depending on the size of any depreciation effect and the rate of re-investment in human capital. This will again be reflected in the shape of the age-earnings profile. The need to encompass these differences has recently been recognised in the literature.

Mincer and Polachek (1974) provides the first formal attempt to model the effect of taking time out of employment not spent in unemployment. One of the aims of their work is to interpret work histories within the context of past expectations and family life (whether current or prospective). This section begins with an introduction to this work and then extends to a coverage of Mincer's later co-authored work in the same field.

Let earnings at time t equal last year's earnings plus, C_{t-1}, the amount invested in human capital in the $t-1$ th period multiplied by the return on that investment, r,

$$E_t=E_{t-1}+rC_{t-1} \tag{4.11}$$

If time out of work leads to the atrophy of skills then the stock of human capital may well be reduced during a career break. Mincer and Polachek define δ_t as the depreciation in human capital in period t, such that, including depreciation:

$$E_t=E_{t-1}+rC^{*}_{t-1}-\delta_{t-1}E_{t-1} \tag{4.12}$$

where C^{*}_{t-1} represents gross investment in human capital in period $t-1$. Gross investments are split into net investments and depreciation where terms marked with an asterisk indicate gross variables.

Rearranging (4.12) yields

$$E_t/E_{t-1}=1+rs^{*}_{t-1}-\delta_{t-1} \quad (4.13)$$

where s^{*}_{t-1} is the gross investment ratio ($C_{t-1}^{*} / E_{t-1}^{*}$). Or, in net terms (4.13) yields

$$E_t /E_{t-1}=1+rs_{t-1} \quad (4.14)$$

By recursion, $E_t = E_0(1+rs_0)\,(1+rs_1)\,(1+rs_2) +\ldots(1+rs_{t-1})$ (4.15)

For period *t*, the return on gross investment is,

$$rs_t=rs_t^{*}-\delta_t \quad (4.16)$$

Substituting (4.16) into the logarithmic equivalent of (4.14) gives

$$\ln E_t=\ln E_0+\sum_{i=0}^{t-1}\ln(1+rs_i) \quad (4.17)$$

which reduce to

$$\ln E_t=\ln E_0+\sum_{i=0}^{t-1}(rs_i^{*}-\delta_i) \quad (4.18)$$

since $ln(1+rs_i) \sim= rs_i$.

Mincer and Polachek adapt (4.18) to calculate the current earnings of workers with consecutive segments of participation and non-participation. Thus,

$$\ln E_t=\ln E_0+(rS-\delta_{,})+(rs_1^{*}-\delta_1)e_1+(rs_h^{*}-\delta_h)h+(rs_2^{*}-\delta_2)e_2+(rs_3^{*}-\delta_3)e_3 \quad (4.19)$$

Here, e_1 and e_2 represent market work completed between school and first child and between the first child and the current job, h is the period of home time in the period between first child and return to work, and e_3 are years on the current job.[4] This specification allows for different returns to experience before and after any career break, together with differing amounts of depreciation on the human capital stock in those periods, and an additional effect, presumably negative, of time out. Using ordinary least squares estimation on 993 white married women with children from the 1967 US National Longitudinal Survey of Work Experience, Mincer and Polachek conclude that the post-

[4] As in the authors' appendix on Page S108.

interruption investment in skills is greater than the pre-interruption investment (as the coefficient on e_3> coefficient on e_1).

Perhaps more interestingly, they find a net depreciation effect during the home time period of 1.5 per cent (via $(h_1+h_2)100$). The length of the home time periods are quite small enabling the home time intervals to be analysed either separately or together with negligible difference in terms of results. Mincer and Polachek choose to drop the usual experience squared term for simplicity.

Mincer and Polachek present one of the earliest assessments of the size of the depreciation effect of human capital resulting from home time and they provoke further debate on the optimum method of modelling such an effect. However, they fail to focus on the possibility of intensive restoration of human capital which takes place on re-entry. This becomes the subject of their subsequent work and it is the central theme for what follows.

4.4.1 The Mincer and Ofek (1982) Restoration Model

The subsequent work of Mincer and Ofek (1982) builds upon previous research and contributes significantly to the literature through the modelling of the rebound period: that period of time in which restoration of human capital may take place upon re-entry. Using cross-sectional retrospective data on a sample of women taken from the 1967 National Longitudinal Survey (NLS), Mincer and Ofek (1982) utilise a standard Mincerian wage equation to analyse these effects by incorporating a variable that measures the length of time out of the labour force as an explanatory variable (h). They distinguish four distinct effects of a break in a worker's employment. First, the normal growth in human capital acquisition (through work experience) is abruptly terminated. They state that real wages are firstly affected by the forfeit of human capital during the break in employment, as it is impossible to engage in the normal accumulation of work-centred human capital whilst a worker is out of the labour market. Second, non-participation causes skills to depreciate or atrophy. For as long as work skills are not being used, these skills waste away and this impacts negatively upon real wages. Third, significant investment in human capital takes place upon re-entry in the rebound phase. Real wages rise substantially due to the heavy

investment in human capital which the worker carries out. Fourth, the normal growth rate is resumed once pre-interruption level of earnings are achieved and this takes place in line with that experienced by the continuously employed worker. Thus, the natural logarithm of the real hourly wage (ln *W*) is regressed, as below

$$\ln W = r_s S + \beta_2 e_0 + \beta_3 e_0^2 + \beta_4 e_1 + \beta_5 h_0 + \beta_6 h_1 + \beta_7 V \qquad (4.20)$$

where *S* are years of schooling, e_0 are years of experience prior to the most recent spell of nonparticipation, e_1 are years of experience after the most recent spell of nonparticipation, h_0 are years of nonparticipation prior to most recent spell of employment, h_1 are years of nonparticipation after the most recent spell of employment, and *V* represents a vector of other individual-specific variables that incorporate the effect of various life events and the impact that they have on the work interruption period h_1. Thus, *V* includes years of last job tenure and dummies for whether the individual married, divorced or had a baby during or immediately before having a career break.

Mincer and Ofek claim that the coefficient on e_0 captures the long run returns to experience and that the coefficient on e_1 captures the more immediate, short run returns to experience. Similarly, the coefficient on h_0 represents the long run effect of nonparticipation whilst the coefficient on h_1 is the short run effect of nonparticipation.

The NLS data is able to provide estimates of the wage equation for US women at the point of their re-entry into the labour market. At this point, the individuals have just terminated their period out of the labour force (h_1), and their years of work experience after the most recent spell of nonparticipation (e_1) is equal to zero. The estimated return to one additional year of education is around 4.5 per cent for all women and is 3.7 per cent for women with intermittent participation. This is less than that found for British continuous female workers of around 7 per cent (Harmon and Walker (1995). More importantly for the purposes of Chapter 5, Mincer and Ofek find that there is a negative and significant impact of engaging in a period out of the labour force on wages. Moreover, the decline in re-entry wages is larger, the more severe the interruption. This indicates a process at work which amounts to more than the simple accumulation of the losses of general and job-specific

skills through lower levels of work experience (see also Table A.4.1 in the Appendix to this Chapter).

Mincer and Ofek (1982) awakened a great deal of interest in the depreciation issue following their publication. From Table A.4.2 in the Appendix to this Chapter, it can be seen that there is evidence of a depreciation effect as a result of a career break in all studies that followed in spite of differences in the nature of the data sets and the difference in time periods analysed. Mincer and Ofek show that despite the rebound period, female returners never achieve the continuous worker earnings profile. The effect of the intermittent participation has a permanent impact on subsequent earnings. Before we are in a position to offer a commentary on the nature of the gender wage gap in Britain, it would seem reasonable to investigate more fully the nature of differences in pay between women with different labour market histories. This we do in Chapter 5. The next section examines in detail another theoretical perspective on female labour market interruptions which uses the foundations highlighted here.

4.4.2 The Groot and van Ours (1994) Transitory and Permanent Effects Model

Groot and van Ours (1994) build on the existing literature on work interruptions using a 1986 data set from the Netherlands containing retrospective information on labour market history together with details of current earnings. Their contribution is mainly an empirical one, but it does shift the focus to whether the effects of interruptions are permanent or transitory, much in the spirit of Ruhm (1991). They are interested in comparing the effects of having time out from work in unemployment in contrast to spells out of the labour force. They acknowledge various factors that affect the stock of human capital over the life cycle. For example, workers switch occupations, lose jobs because they quit or are fired, and re-engage in education. Groot and van Ours (1994) wish to disentangle career interruptions of different natures in order to draw conclusions about the possibility of different transitory and permanent effects. They utilise the Mincer and Polachek (1974) separate time periods distinction and stress the importance of a rebound effect in work following time out, during which all the re-investment in human capital is assumed to take place. They estimate their

model separately for males and females and separate returners according to the state in which they were present prior to returning to work.

The following work experience equation is developed

$$X_i=Em_i+\beta_3 U_i+\beta_4 O_i+\beta_5 R_{u,i}+\beta_6 R_{o,i}+\beta_7(T_i-R_{u,i}-R_{o,i}) \qquad (4.21)$$

where X_i is the total amount of work experience, *Em* is work experience before job loss or in the current job for those without an interruption, *U* is the length of the last unemployment spell, *O* the length of an out of labour force spell, R_u the rebound period in work following unemployment, R_o the rebound period in work following time out of labour force and *T* is tenure in the current job net of the rebound period.[5] It is expected that the coefficients on the unemployment and inactivity terms, β_3 and β_4 respectively, will be smaller than β_7, (the coefficient on job tenure adjusted for the rebound period). This would indicate that human capital formation during the period of unemployment is less than that acquired on-the-job. If β_3 is negative, then this would indicate that destruction of human capital takes place during unemployment spells. If β_4 is negative it would again indicate the destruction of human capital, but this time, as a result of time spent out of the labour force. Evidence of any permanent negative long-term wage effect of an interruption requires not only the negative effect of atrophy from time out, but also a sufficiently large negative effect to offset any earnings gains made during the rebound period. Groot and van Ours (1994) motivate this comparison by investigating the adjusted coefficients β_3, β_4, β_5, and β_6 as follows. They envisage two workers, *j* and *k*. Worker *j* has a period out of the labour force and then recommences work, such that O_j+T_j describes her work pattern. Worker *k* has an identical previous history to *j* but begins a new job at the start of the time period in which *j* begins her O_j. Thus,

$$O_j+T_j=T_k \qquad (4.22).$$

It is assumed that the length of the rebound period is equal to twenty-four months,[6] so that

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[5] All time periods are measured in months.

[6] This was chosen arbitrarily to coincide with the length of time of the probation period for a new worker in the Netherlands.

$$Em_j+\beta_4 O_j+\beta_6 24+\beta_7(T_j-24) = Em_k+\beta_7 T_k \quad (4.23)$$

Substituting T_k from (4.22) into the above yields

$$\beta_6 = \frac{(\beta_7 - \beta_4)O_j}{24} + \beta_7 \quad (4.24)$$

In the absence of any long-term wage effects, β_6 would equal zero given current tenure in excess of twenty-four months. Let

$$\beta_6^* = \beta_6 - \frac{(\beta_7 - \beta_4)O_j}{24} - \beta_7 = 0 \quad (4.25)$$

so that a long term wage effect as a result of a spell out of the labour force shows up in β_6^*. This expression may be intuitively understood from rearranging as follows:

$$(\beta_6 - \beta_7) - (\frac{\beta_7 - \beta_4}{24})O_j = 0 \quad (4.26)$$

This holds when there is no long-term wage impact. In effect, this is saying that the positive contribution due to rebound (β_6) adjusted for the smaller tenure coefficient (β_7) will be greater than zero (that is, β_6-$\beta_7 > 0$). However, when the impact of O_j exactly counteracts this effect, the whole expression will equal zero. *A priori*, it is expected that taking time out of the labour force incurs long-term costs such that the positive amount resulting from β_6-β_7 is overshadowed by $\frac{\beta_7 - \beta_4}{24} O_j$ and the expression becomes negative. Groot and van Ours investigate whether or not the expression for β_6^* is indeed negative. If this is so, then it is indicative of a negative long-term effect on wages as a result of intermittent participation.

Groot and van Ours (1994) draw the following conclusions. There are no long-term negative wage effects following either type of interruption for male workers, because $\beta_5^*=\beta_6^*=0$. Further, there are no long term wage effects for a period of unemployment for females, as β_5^* is not significantly different from zero.

However, they find that there is a permanent long term wage effect following a period out of the labour force for females, (that is $\beta_6^*<0$). Groot and van Ours (1994) point out that

the average length of interruption due to a period out of the labour force is 4.5 years, whilst the typical length of an unemployment spell is 4 to 5 months. They suggest that when a break occurs, if the interruption is short, then the earnings effect will be transitory.

4.5 Conclusion

Despite over two decades of theoretical and empirical work mainly in the United States, the empirical evidence on the interaction of human capital, earnings and labour supply in Britain is still comparatively rare. The following Chapters seek to rectify this deficiency. The theoretical literature would seem to suggest that time spent out of the labour force has negative consequences for subsequent earnings, after controlling for both observed and unobserved heterogeneity across individuals. The existence of any wage effects from time out will have direct implications for the gender pay gap. It is also notable that household factors, such as the presence of children, would be expected to influence labour supply decisions. This is an issue to which we turn in Chapter 7.

The Groot and van Ours (1994) approach has the following advantages. First, it allows for two different types of interruption to be analysed contemporaneously (namely, unemployment and time out of the labour force). Second, the model enables the investigation of both short and long term wage effects. The Groot and van Ours framework contributes to our understanding of the impact of career interruptions for workers in the Netherlands. The use of British data enables the evaluation of similar effects in another European country.

This whole area provokes exciting research questions. It would seem that the depreciation effect may not be the whole explanation for the low re-entry wage. Indeed, there might be some role for a signalling mechanism within the framework. In other disciplines, issues involving the signalling of commitment to the workplace through continuous participation has received much attention. It would also be interesting to incorporate the impact of the part-time and full-time work decision into the analysis, as in Jones and Long (1979). Chapters 5 and 6 present new empirical evidence on the issues of work interruption and earnings, while Chapter 7 takes analyses the return to work decision in more detail.

Appendix 4

Table A 4.1 Withdrawal and Re-entry Wage Rates by the length of the Interruption Period

	Years of Non-participation			
	<1	1-2	3-4	5-6
Withdrawal hourly wage rates ($)	2.27	1.92	1.70	1.73
Re-entry hourly wage rates ($)	2.35	1.75	1.46	1.27
No. of observations	931	128	141	104

Rates are at 1967 prices. Data from the NLS for married women (ages 30-44 in 1967)
Source: Mincer and Ofek (1982), page 7.

Table A 4.2 Empirical Studies on the Wage Effects of Intermittent Participation

Authors(Year)	*Data Set Used*	*N*	*Annual Negative Effect of Break (%)*	*Rebound analysis*
Mincer & Polachek (1974)	NLS USA1967	993	1.5	no
Sandell & Shapiro (1980)	NLS USA1967	969	< 0.5	no
Corcoran & Duncan (1979)	PSID USA1975	1326	0.5	no
Mincer & Ofek (1982)	NLS USA1967	1015	7.6	yes
Corcoran,Duncan & Ponza (1983)	PSID USA1969	821	3.3	yes
Groot Schippers & Siegers (1990)	CBS Netherlands1982	211	0.3	no

Chapter 5
Interrupted Work Careers and Earnings: Some New British Evidence

5.1 Introduction

In Chapter 2, we catalogued the changing patterns of female participation and wages in Britain. We indicated that there were substantial differences in employment rates amongst women and highlighted the importance of family status, in particular the age of the youngest child, in influencing these rates. Despite the rapid increase in employment rates for women with young children over the past twenty years, it remains the case that women with young children are still nearly 50 per cent less likely to be in work than other women. Moreover, the wages of those women with young children who are in work seem to be lower than for other women. It is important, therefore, to investigate the relationship between labour market participation and wages in more detail. Since the General Household Survey, (GHS), used in Chapter 2 does not contain any detailed information on an individual respondent's labour market history, this Chapter examines this theme using evidence from another British data set which does contain relevant information: the National Child Development Survey, (NCDS).

Waldfogel (1993) demonstrates how much of the gender pay gap is attributable to family status, principally the presence of young children, through use of both the NCDS and the GHS. Her work provides some support for the conventional human capital explanation of wage differentials between the genders, whereby the lower wages earned by working mothers relative to men are linked to their lower levels of work experience. Moreover, she finds that the mothers in her sample are subject to a small wage penalty whether or not they have a career break longer than that afforded by statutory maternity leave. The work in this Chapter builds on this foundation looking at the wage differences between women, rather than across gender, conditional on work experience in more detail. Further, we emphasise the importance of allowing for differences in the nature of the non-work spells in the impact on earnings.

In Section 5.2, we first investigate the average spell lengths in and out of work for the NCDS cohort and examine how this differs across sub-groups of women. We then split time spent in work into full-time and part-time spells and time out of work into time

spent in home production, unemployment, education and a residual category. In Section 5.3, we estimate the impact of a withdrawal on the wages of these women. Further, we assess how various lengths and types of home time affect the wage impact of withdrawal and how this links to the levels of the intensity of participation. One advantage of the NCDS data set is that we can use precise measures of female labour market experience, both in work and out, (and forego the usual approximation of potential experience frequently used in earnings equations) in order to offer insight on the rate of return per year of realised work experience. We are also able to analyse how spending time in domestic responsibilities compares with other non-work activities, as valued by the subsequent re-entry wage, in a bid to determine the depreciation effect of human capital. If we can associate different wage penalties to the various types of break for the same duration of out spell, this would suggest that a simple human capital depreciation story is not the full explanation. Therefore, in Section 5.4, we concentrate on issues of selectivity in an attempt to assess whether the observed penalties to time out vary when potentially endogenous selection into the labour force is accounted for. We use the basic Heckman (1979) selectivity correction technique applied to the case of endogenous dummy variables and the Lee (1983) extension (which allows for multiple selection outcomes). Section 5.5 includes first difference estimation in order to control for any unobserved heterogeneity that may otherwise bias any observed time out penalties. Section 5.6 concludes by throwing light on the differences between various groups of women found in the Chapter and sets the scene for the analysis of how the groups of continuous and intermittent workers may be subsequently compared across the genders in Chapter 6.

5.2 British Evidence on Labour Market Histories

We now present our own, new evidence for Britain of the effect of labour market interruptions on subsequent earnings using the NCDS data set. The NCDS data follows a cohort over time. Within the cohort it is likely that there will be variations in the number of interruptions, the length and timing of interruptions and in the type of interruption. Some women may have held only one job throughout their career, others may have had multiple jobs. Time out of work might have been spent in unemployment, home production, education or some other activity. Note that the NCDS encourages mothers to include any maternity leave as part of a continuous spell

of employment. Time in employment may have been in either part-time or full-time work. The relative importance of these different spell types is still not well known. This section begins, therefore, with an examination of the distribution of these interruptions across our sample of women and across selected sub-groups.

Table 5.1 shows that the mean number of jobs held by the NCDS cohort since leaving full-time education is 4.2. There seems to be some difference in work history patterns according to whether women are in work in 1991 or not. The average number of jobs held by women in work is slightly higher at 4.5 jobs. For the whole sample, just 1 per cent have never had a job by the age of thirty-three. For the sample in work, when split by marital status and the presence of children at the age of 33, lone parents, on average, have held the largest number of jobs, (a mean of 5.1 for those in work), whereas married women have held the least (a mean of 4.3 for those in work). The spread for working women is rather large: just over 12 per cent have had 8 or more jobs by the age of thirty-three whilst a similar number have had only one job. For the sample of women as a whole, the lack of a partner is associated with more jobs. However, for the sub-sample of women in work in 1991, this correlation is not so strong. There are no obvious differences between married women with and without children or single childless women. Only lone parents in work in 1991 have held more jobs than the average.

Table 5.2 summarises the work history patterns by duration of each spell type for those women in work in 1991. We present the frequency distribution of non-work spells alongside the mean duration of spells spent in work (in both full- and part-time work), the mean duration spent out of work since leaving education, and the duration spent in work before and after the most recent break. Standard deviations are given in parentheses. The duration calculation covers all spells from leaving full-time education to the time of interview and so include all completed spells together with the most recent spell of work or non-work in progress. Since the women in the NCDS sample are all of the same age, the differences in the time spent in and out of work will be partly accounted for by differences in the age at which the women left full-time education. There may also be differences in labour market experiences after leaving full-time education which will also contribute towards duration heterogeneity in the sample.

Table 5.2 shows that approximately 38 per cent of women have worked continuously since leaving full-time education, with a mean duration of 14.4 years. The majority of women, however, have experienced some interruption to their work career by the age of thirty-three. Around 33 per cent of those in work record just one spell out of a job and nearly 12 per cent record three or more out spells. These figures are similar to the findings of Stewart and Greenhalgh (1984) for a cohort of women aged between 25 and 34 years of age observed in 1976. For example, they found that around 34 per cent of their cohort had worked continuously.

The mean duration of work experience falls with the number of periods spent out of work, from 14.4 to 10.7 years between the 0 and 3 plus non-work spells categories, (column II). The majority of work experience consists of full-time work (column VI), but this relative dominance tends to fall with the number of spells out of work. Indeed, part-time work experience increases with the number of non-work spells, (column VII). This suggests that full time work is a closer substitute for time out than part time work. Table 5.2 shows that the mean duration of non-work rises by approximately one year for each additional out of work spell (column IV). The mean duration spent in full-time work falls by approximately one year, confirming that time out of work takes the place of full- rather than part-time work. Even so, the mean duration of all spells of part-time work experienced by the age of 33 is around 2.5 years, around a quarter of the total amount of full-time work experience at the same age.

Not surprisingly, the mean duration of time out also increases with the number of non-work spells, from 3.4 to 5.3 years between the 1 and 3 plus non-work spells categories, (column IV). We also divide total work experience into the time spent in work before and after the most recent outspell. The division of these spells is reasonably even so that the last break occurs approximately halfway through the women's work history up to 1991. The average duration of work experience since the last non-work spell, (column V), falls with the number of non-work spells.

Table 5.3 examines the employment histories of those women out of work in 1991. Just 2 per cent of non-working women have never worked by the age of 33, whilst 44 per cent have had one continuous spell out of employment with an average duration of 6.4

years (column IV). Around one quarter have experienced three or more non-work spells. Thus, women who were not in work in 1991 are more likely to have had multiple non-work spells than women in work, and, for each given number of breaks, the duration of non-work is longer. It could be the case, therefore, that these women are systematically different from those in work in 1991. We return to this issue in Section 5.5.

The majority of time spent out of work, as shown in Tables 5.4 and 5.5, is spent in home production, (around 64 per cent of the total). By the age of 33, the average duration spent in home production is around 1.6 years for working women and 6.8 years for women not in work in 1991. Women in work in 1991 had experienced an average 4 months unemployed and 6 months in further education (or training) since leaving full-time education. The shares of time spent in education and unemployment do however rise with the number of spells out of work. This suggests that multiple spells are more likely to consist of a combination of these events. Women not in work in 1991 had experienced around twice as much unemployment over their lifetime as women in work.

We now examine whether work history patterns vary across different groups of women. We distinguish by marital status and by full- and part-time status, for the sample of working women only. Not surprisingly, single, childless women are more likely to have worked continuously (48 per cent, against 36 per cent of married women and 34 per cent of lone parents), and to have had fewer interruptions (Tables 5.6 to 5.9). Moreover, any interruptions tend to be of a shorter duration for this group. Lone parents have the most interruptions and longer durations of spells out of work. Part-time work seems to be more common amongst lone parents and married mothers with children than the other groups. Married women with children, however, behave in a fashion that is very similar to the group of married women as a whole (Table 5.9).

Table 5.10 (a) confirms that full-time work is much more likely to be associated with continuous work experience. Nearly 50 per cent of women in a full-time job in 1991 have worked continuously (and most of this has been spent in full-time work) compared to less than one quarter of women in part-time work, for whom part-time work accounts for less than half of their work experience. Part-time work intensity seems to be

associated with more recent female returners for any given number of non-work spells (the post-break durations are shorter for part-timers compared to full-timers). Table 5.10 (b) divides total work experience into the length of time spent in full-time and in part-time work, before and after the last break. The Table confirms that the majority of work experience by the age of 33 is spent in full-time work, (compare columns I and II), but that part-time working appears to be more common after time out, (compare columns IV and VI, particularly for those with one non-work spell).

We have, then, for NCDS women, the general picture that by the age of 33, nearly 90 per cent of women will have held at least 3 jobs, (Table 5.1) and more than 60 per cent of women will have had a spell out of work, most probably spent in home production, (Table 5.2). Their work history will consist of a combination of full-time and part-time work, with the majority of it spent in full-time work, but with part-time working becoming relatively more likely after a break and more likely the greater the number of spells out of work. Our main focus in this Chapter, however, is with the effect of work interruptions on the earnings of women. It is to this issue that we now turn.

5.3 Employment, Interruptions and Earnings

We begin with some summary statistics. For the sample of women in work in 1991, Table 5.11 gives mean real hourly and weekly wages conditional on the length of time not in work. The Table illustrates that hourly and weekly wages fall with the duration of interruption for both women in full- and in part-time work. For example, the average weekly wages of those who have had 4 years or more out of work by the age of thirty-three are some 52 per cent of those who have been in work continuously. Some of this weekly wage gap is fuelled by the differing incidence of full- and part-time work across the groups. The mean hourly wage gap is around 68 per cent. Around 22 per cent of continuous workers are part-time, whilst 60 per cent of those with a 4 year plus out spell are part-time workers. It is apparent from the second and third panels of Table 5.11 that the wage penalty (weekly and hourly) from labour market interruptions is similar for full-time workers as for part-time ones. The mean hourly part-time wage for 4 year plus returners is some 84 per cent of the uninterrupted part-time wage. The mean hourly full-time wage for 4 year plus returners is also 84 per cent of the uninterrupted full-time wage.

Table 5.12 shows the wage variation by the number of withdrawals. Whilst the standard deviations for the panels are large, we observe that there is less of an average wage penalty from repeated spells out of work compared with the penalty to the length of time out. The length of time out of work has more of an impact on wages than the frequency of interruptions.

Mincer and Ofek (1982) were the first to suggest the possibility of a rebound effect following re-entry to work after a break. They suggest that wages may grow faster relative to continuous workers after the subsequent return to work. This they attribute to the effect of attempts at restoration of previously eroded human capital. Table 5.13 shows that there does appear to be evidence of a restoration effect following work interruption in the NCDS sample. The Table compares the average weekly and hourly wages for women by the length of time since the last non-work spell. Average wages are much lower for those with less than two years back in work compared with continuous workers (see columns I and II). Mean hourly and weekly wages can then be seen to approach the earnings of those who work continuously after a duration of time spent back in work of approximately 6 years (compare columns I and V). This is a slightly longer duration than the five-year period noted by Mincer and Ofek (1982) and the two years assumed by Groot and van Ours (1994). This aggregate pattern is again influenced by the shares of full- and part-time work in the different duration groups. However, both the rebound period and the size of the relative earnings decline are similar for women both in full- and part-time work in 1991. Note that these results may of course, be affected by selectivity issues arising from women choosing to take time out – an issue to which we turn in Section 5.4.

Table 5.14 repeats the above procedure, but focuses solely on those women whose last non-work spell was in domestic duties: where selection issues may be more relevant due to the possible voluntary nature of this state. The comparison of Tables 5.13 and 5.14 illustrates that the effect on wages of a break spent in domestic responsibilities is much larger than for other types of break, particularly in the case of full-time workers (compare the maximum drop in hourly wages of 23 per cent and 47 per cent in the final row of Tables 5.13 and 5.14). Relative to those workers who remain in work, those

with a home break do not attain similar wage levels even after 6 years back in employment. Some of the aggregate differences appear to be driven by the move from full-time work into part-time work after a home time spell. However, even for those returning to full-time work, there exists a large average hourly pay gap (of around 40 per cent at the 6-year stage), relative to continuous full-time workers.

The evidence above suggests that workers with intermittent participation receive wages that are lower than their continuous counterparts. This suggests two possible explanations. First, these women with time out are fundamentally different (perhaps as a function of lower human capital) and would always have commanded lower wages even with continuous participation. Second, time out affects wages negatively, either because of depreciation in human capital or because time out is interpreted as a signal for less committed workers by employers. The next section sets out a more rigorous investigation of this issue using regression analysis.

5.3.1 Estimation

Do women suffer wage penalties from taking a career break? Mincer and Ofek (1982) find a negative effect from time out in the United States of around 1.5 per cent a year on earnings. How does this figure compare with that for women in the UK? The next subsection provides regression estimates using information from Sweep 5 of the NCDS data set. The sample consists of 4574 observations on women who are in work at the time of Sweep 5 and who give current job wage information, of which around 1809 are continuous in their work history and some 2765 women have interrupted work histories. Women in self-employment are excluded, as are outliers observations from employees earning less than 5 pounds a week or more than 6 thousand pounds a week. Those with inconsistent job history information, that is, those with self-reported total work experience greater than the feasible maximum (of 18 years), or those with erroneous job start and finish dates in their histories are also excluded. (See Chapter 3 for more details.) The dependent variable in all regressions is the log of the real hourly wage indexed to January 1992 prices. All specifications are therefore of the log-lin form. This means that the estimated coefficients may be interpreted as the percentage change

in wages (not log wages) given a unit change in the explanatory variable.[1] Table 5.15 gives the sample means of the variables used in the regressions, for the total sample, and for the subset of women who experience a spell in home production. The mean hourly wage for the whole sample is £6.95, which compares with a mean hourly wage for women with home time of £4.56. The mean number of weekly hours for all women in work in 1991 is around 32. Thirty five per cent of the sample are in part-time work. Those women with a spell of home time are more likely to be married, to have children and to have lower educational qualifications. They also tend to work in part-time, less skilled, non-manual and manual jobs in smaller, non-unionised firms. Since these factors are all associated with lower wages, they may help to explain the difference between the two wages.

Potential and Actual Work Experience

One of the advantages of working with longitudinal data is the ability to observe actual rather than potential work experience histories.[2] The NCDS contains retrospective job history information between successive sweeps. Whilst retrospective information may be subject to recall bias (Elias (1991)), the reported histories do allow us to assess the bias resulting from the use of potential experience in standard human capital models. Potential experience is typically calculated by subtracting the age at which the respondent left full-time education from the age at time of interview. The differences in the length of time spent in education would then give rise to a variation in potential experience in the sample. However, the use of potential experience is particularly problematic in our sample since there will be less variation in this variable, (because every female is the same age), compared to other data sets sampled across the population. From Table 5.15, it seems that the potential experience overestimates actual work experience by around 3 years (mean 15.8 years against mean 12.9 years in 1991). It is also clear from Table 5.16 that the use of potential experience biases the estimated returns to experience upward. One year of additional potential experience is associated with a return of 21 per cent. One year of additional actual work experience generates a return of 5 per cent. The cumulative effect of these different returns is that a woman

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[1] Strictly this percentage interpretation only applies to small coefficients.

[2] Johnson and Makepeace (1997) note the importance of lifetime histories, although their focus is the examination of lifetime earnings (rather than the analysis of current earnings).

with 17 years of experience, (near the maximum in our sample), will have earnings 64 log points higher than a woman with 1 years experience on the actual measure, but earnings more than 87 log points higher when using the potential experience measure, other things equal.[3] These estimates do not control for other characteristics. However, this is sufficient to highlight the danger of using potential experience in work of this kind and in the rest of what follows, we use actual work experience.

5.3.2 Empirical Specifications

We begin with a basic human capital specification with a quadratic in experience and dummy variables for the level of educational attainment, and then test for the robustness of the estimates to the addition of extra controls, and the functional form of experience. Unless otherwise specified, all statistical tests are carried out at the 95 per cent confidence level. We use educational qualifications (degree, technical, 'A' level, 'O' level, low, and no qualifications (the default category)) rather than a measure of years of schooling, as the results in this section show that the returns to educational attainment are non-linear and rise in discrete steps. Due to the concerns raised over the issue of unobserved ability biasing the returns to education and experience, we include information on the cohort member's ranking in a test of reading skills at the age of seven[4] to try and capture any ability effects. We include dummy variables for the presence of children and the presence of a child under the age of 4 years. Since the presence of children will reduce the amount of work experience accumulated, any effect from these two variables will capture the additional possible effect of children on reservation wages, having controlled for the effect of having children via lower work experience. We also include ten dummy variables for the region of residence (North, North-West, Yorkshire and the Humber, Wales, West Midlands, East Midlands, East Anglia, South West, Scotland, with London and the South East as the default category). Other controls include marital status, one-digit industry dummies and workplace controls for membership of a union (or staff association), part-time working, the private sector, and establishment size over 50 employees. Autor, Katz and Krueger (1997) highlight the importance of the use of computers in driving wage determination,

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[3] Compare $.234*17 - .01*(17)^2 - (.234*(1) - .01*(1)^2) = .866$ using potential experience with $.054*17 - .0008*(17)^2 - (.054*(1) - .0008*(1)^2) = .637$ using actual experience coefficients in Table 5.16.

[4] Use of a similar ranking in mathematical ability at age seven did not prove significant.

possibly as a proxy for unobserved skill. We therefore include the use of a visual display unit at work amongst the set of controls.

Table 5.17 shows that the estimated coefficients for the basic wage equation (column I) are consistent with those found in the literature. The addition of controls (columns II and III) halves the estimated returns to work experience from 5 to 2.5 per cent a year.[5] The positive returns to educational attainment with respect to the reference category are similarly reduced. A graduate member of the cohort earns around 30 per cent more than an individual with no educational qualifications, (the default category). The inclusion of current job tenure, as an additional control for firm-specific capital, does not affect the general pattern of results. The estimated return to one extra year of job tenure is around 0.7 per cent (column III) and the other coefficients are changed little.[6]

The remaining controls behave as expected. Wages are seen to be around 9 per cent higher for those in the unionised sector, whilst wages for part-time workers are around 28 per cent lower, (in column III). Interestingly, the use of a visual display unit at work is associated with a 20 per cent pay reward. This could be indicative of unobservable skill differences for those workers who have the capacity to use new technology or it may simply reflect the lack of occupational controls.[7] The individuals in the bottom fifth of the reading ability distribution at the age of seven earn around 7 per cent less than their counterparts in the top fifth, other things equal. Women with children under four command earnings that are around 12 percent higher than the earnings of women with older children, but around 4 percent lower than the wages of women without children, (the sum of the coefficients on *kids* and *young kid*). This is almost certainly because only high-wage women can afford the high childcare costs of very young children (an issue which also arises in Chapter 6 using the BHPS data).

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[5] The F-test at a conventional 5 per cent level of significance for the validity of the inclusion of the extra variables given by
$F = [(RSS-URSS)/J] / URSS/(n-k) = [(1236.9-926.3)/31] / 926.3/(4574-38) \sim F(31, 4536) = 50.1$
$F_{95}(31, 4536) = 1.46$, is accepted.

[6] To the extent that the controls for ability and the use of computers do not capture fully the impact of unobservables, then the coefficient on job tenure may be biased. See Topel (1991) for an alternative method of dealing with this issue using panel data. The NCDS data set does not allow this because the wage at the start of the current job is not observed.

[7] The vdu result is robust to the inclusion of one-digit occupational controls, but we choose to work without such dummies due to concerns that their incorporation in a wage equation would be too deterministic. Knowledge of a woman's occupation will give a fair indication of that person's wage.

Table 5.18 first tests the functional form of experience by including first, higher order polynomials (column I), second, splines with knots at 12 and 16 years (column II), and finally, dummy variables for each year of experience (column III). The cubic specification suggests that the usual quadratic may not fully capture the relationship between experience and earnings.[8] The spline specification encapsulates the relationship in a slightly different form. It estimates the wage equation with three dummies to represent different levels of experience, and constrains the estimation to be continuous at the knots. The coefficients measure the change in slope from the preceding spline and are therefore additive. The spline function suggests that those individuals with intermediate amounts of experience (between 12 and 16 years) earn less than others. This is confirmed by the dummy variable specification of column III. Earnings are highest among those with eleven to twelve years of work experience. This may reflect the additional impact of a degree qualification that is not fully captured by the graduate dummy variable. Since these specifications are not nested, the dependent variable is the same, so we can look at the adjusted R^2 to compare the goodness of fit. The specification that includes the experience dummies proves superior in fit, but the difference in the adjusted R^2 is not large relative to the quadratic specification. We proceed with the latter in what follows.

Full- and Part-time Experience

The summary statistics in Table 5.11 and 5.12 suggest that part-time status reduce hourly earnings. Stratton (1995) suggests that failure to account for differences in earnings between full- and part-time jobs may bias upwards estimates of any depreciation in human capital resulting from time out of work, if part-time work carries a pay penalty, and more women return to part-time work after time out. The final column of Table 5.18, therefore, splits the total work experience into its full- and part-time components.[9] The results indicate that all the returns to additional experience are confined to full-time work. Additional years of part-time work experience do not raise earnings. Later, Table 5.20 goes on to include the length of time not in work along with the split of total work experience into its full- and part-time components. Once more,

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[8] Murphy and Welch (1990) arrive at a similar conclusion using U.S. data.
[9] Part-time working is self-defined by respondents.

we witness that positive returns to work experience are only associated with a return to full-time work.

5.3.3 The Restoration Model

Tables 5.11 to 5.14 established the existence of the negative impact of a work interruption on wages. This section seeks to analyse the nature of the time out effect more closely. Initially, we follow the methodology set out in Mincer and Ofek (1982).

Pre- and Post-gap Work Experience

In our data, some of the women who have experienced a break from work in the past have been in their present job for some time. Mincer and Ofek suggest that renewed participation in paid employment triggers the restoration of skills lost while out of work. We would expect then that the negative effect of a withdrawal from the labour market on earnings is moderated by time spent back in work. However, whether the earnings of an intermittent participant catch up with those of a continuous worker is debatable. Later, in Chapter 5, we present additional evidence as to why earnings for those with a break do not reach the same level. Here, we begin to address this issue by splitting the total work experience term into pre-gap and post-gap work experience, where the gap referred to concerns the most recent break. Since total work experience (*totspell*) is the sum of pre-gap work experience (*preout*) and post-gap work experience (*postout*) we have *totspell=preout+postout*, such that the wage equation in Equation (4.20) can be rewritten as

$$\ln W = \beta_0 + \beta_1 \text{preout} + \beta_2 \text{postout} + \beta_3 (\text{preout} + \text{postout})^2 + \gamma V \qquad (5.1)$$

Expansion of the term in parentheses leads to

$$\ln W = \beta_0 + \beta_1 \text{preout} + \beta_2 \text{postout} + \beta_3 \text{preout}^2 + \beta_4 \text{postout}^2 + 2\beta_5 \text{prepost} + \gamma V \qquad (5.2)$$

where *prepost* is the interaction term generated from multiplying pre- and post-gap work experience and *V* represents a vector of individual-specific variables. This specification suggests the possibility that the returns to work experience before and after the last break may vary. Table 5.19 (columns I and V) reports the results from replacing actual work experience in this way. The coefficients on the squared terms are not restricted to

be equal. The levels of work experience for those with no recorded gap are included in the pre-gap experience terms. The second set of results in the table, (columns V to VIII), are for the sub-sample of women who have experienced some spell out of work. The results confirm that the impact on wages of the most recent work experience obtained after a break (*postout*) is larger than that of the pre-gap work experience (*preout*) (for the sample of all female workers and the sample of all workers with a break, respectively). The coefficients on experience, their squares and the interaction term imply that the effect of one year's experience after a break increases earnings by around 3.1 per cent, whilst one year's experience before a break raises current wages by around .008 per cent (column I), or by 5 per cent and 1.1 per cent respectively (column V). Columns II and VI use total time out of work rather than total time in work as a proxy for experience. The results suggest that one year of time spent not in work reduces earnings by around 1 per cent.

At the interview survey date for Sweep 5 in 1991, for our sample of working women, we have constructed the duration of the length of the most recent spell out of work (h_1), the sum of the length of all other spells out of work (h_0), years of work experience after the most recent spell of nonparticipation (e_1), together with current job tenure and years of work experience prior to the most recent break (e_0) following the general form:

$$\ln W = r_s S + \beta_2 e_0 + \beta_3 e_1 + \beta_4 h_0 + \beta_5 h_1 + \beta_6 V \qquad (5.3)$$

Columns III and VII of Table 5.19 demonstrate that the coefficient on years spent out of work is robust to the inclusion of pre- and post-gap experience. Post-gap experience continues to have more of a positive impact on earnings. Columns IV and VIII estimate Equation (5.3). The coefficient on the last interruption period, h_1, is negative and significant, for the total sample of women and for the sub-sample of intermittent workers. In line with Mincer and Ofek (1982), we find that previous non-work spells do not have such a severe impact on earnings as the most recent period of non-work. The short run negative effect on wages of the last non-work period, h_1, ranges between 1.6 and 2.1 per cent a year depending on the sample. However, the negative effect on wages of the total duration of all previous non-work spells, h_0, is estimated to range from 0.3 to 1 per cent per year. Tenure in a job in 1991 accounts for some of the re-entry rise in post-break wages. For our total sample of women, current job tenure raises the wages of

the combined sample by 0.6 per cent at the mean. This is in line with the Mincer and Ofek interpretation of the appreciation in real wages following a return to work that highlights the rapid re-acquisition of lost skills.

Table 5.20 includes both total work experience and out of work experience in the same specification, (columns I and III). The effect is to reduce the estimated return to work experience by around 1 percentage point to around 1.5 per cent a year, (compare column I with column III in Table 5.17). Note also that one year out of work, on average, reduces current earnings by more than one year's additional work experience. This suggests, however, that it may not be the case that time out of work can be modelled simply as a reduction in the amount of total work experience. There may be additional effects and it is important to allow for these in wage equations. We return to this issue and discuss the possible causes of this finding in Section 5.3.4 and Section 5.4.

In order to continue to assess the hypothesis contained in Stratton (1995) that failure to distinguish between full-time and part-time work experience may overestimate the penalty to time out, we compare the results in column I with a specification that splits total work time accordingly (column II). The exercise is again repeated for the sub-sample of women with a career break (column IV). Column I includes a dummy variable for part-time working. The estimated coefficient for this variable indicates that hourly wages are 27 per cent lower for women in part-time work, consistent with the findings in the overview in Chapter 2. When actual experience is split into full and part-time work experience, the results show that all the positive returns to work experience accrue to full-time work experience. The F tests for equality of coefficients on the part-time and full-time experience variables are rejected at the 95% significance level. There appear to be significant negative wage returns to part-time working in both samples of women. This may explain why the gender wage gap for women in part-time work, observed in Chapter 2, has widened relative to men and women in full-time work over time. There appear to be no gains to part-time, only to full-time work experience.

Distinguishing between different types of periods spent out of work

Once an individual has had a break from continuous employment, the cost of this is long-term and far-reaching. If we view this loss as a result of the erosion of job-specific

skills, then we would expect a similar process whatever the nature of the non-work break. If, however, the worker decides to invest in education and this is later to be rewarded in the labour market, then the negative impact of a break may be outweighed on re-entry. Equally, unemployment may scar workers more than a spell in home production.[10] This section explores the impact on wages of breaks spent in education, unemployment or some other activity in addition to spending time in domestic duties.

Table 5.21 shows that the negative impact of time out of work observed earlier is confined to breaks spent in domestic duties, unemployment and sickness (or disability) or the other, catch-all, category. One additional year spent in a period of unemployment reduces wages by some 7.9 per cent, whilst one extra year spent in a period of domestic duties reduces wages by some 4.6 per cent. These effects are statistically significantly different according to the standard F test for equality of the regression coefficients on the levels and squares of the unemployment and home time variables, although this is not the case for the sub-sample of women excluding continuous workers. In contrast, a year in education raises earnings by some 6 per cent, (column I). This indicates that breaks that could be expected to enhance human capital have precisely the expected effect on earnings. The addition of controls for actual work experience raise the penalty on unemployment, home time and other, unspecified breaks further (column III).[11]

5.3.4 Short run and Permanent Effects of Breaks

The NCDS data set enables us to distinguish between career interruptions of different types and to analyse the transitory effects of such career breaks. Table 5.20 suggests that one year out of work does not have an equal and opposite effect to one extra year's work experience in a wage equation. Furthermore, as Table 5.21 shows, the type of interruption affects the size of the earnings penalty. We now examine whether the interruption type also matters for the rebound effect. We commence with a version of the Groot and van Ours (1994) model, where all interruptions are grouped into a single time out category. We later split this into the four non-work types used above. In this latter case as explained in Chapter 4, total experience for individual *i* takes the form:

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[10] See Ruhm (1991) for a discussion of scarring.

$$totspell_i=preoutsp_i+\beta_2 U_i+\beta_3 O_i+\beta_4 H_i+\beta_5 Ed_i+\beta_6 R_{u,i}+\beta_7 R_{o,i}+\beta_8 R_{h,i}$$
$$+\beta_9 R_{ed,i}+\beta_{10}(T_i-R_{u,i}-R_{o,i}-R_{h,i}-R_{ed,i}) \quad (5.4)$$

where *totspell* is the total amount of work experience, *preoutsp* is the experience before job loss (or total work experience in the case of continuous female workers), R_j the rebound period following re-entry from state *j*, and *T* is tenure in the current job. Groot and van Ours (1994) assume the length of the rebound period is 24 months, because this is the maximum length of probation in new jobs in the Netherlands during which time workers may be dismissed with out notice. In Britain, at the time of our sample, a similar probationary period pertained to full-time jobs. The qualifying period for part-time jobs was five years.[12] We, therefore, work with the 24 months constraint and test for whether the coefficient on this rebound period is different from the coefficient on current tenure net of the rebound.

Table 5.29, column I, presents the simple version of the model. The results confirm our earlier findings that destruction of human capital takes place, as a result of time spent out of work. The short run negative effect on wages of the last non-work period, h_1, is 2.0 per cent a year. The rebound effect is not significantly different from the effect of subsequent tenure in the current job, (witness the confidence interval implied by the standard error on *rebound*). Column III indicates that both the penalties to time out and the rebound effect differ when we control for the type of break. The rebound effect is positive and strong after periods spent in education and the other, unspecified category. Again, according to the conventional F test, there appear to be significantly higher penalties for the last unemployment spell than for the last home time spell. There is no evidence of a rebound effect for those whose last break was spent in unemployment or home production. The coefficients on these two variables are individually insignificant and jointly statistically undistinguishable.

5.3.5 Diagnostic Checks

Before proceeding further, we assess the sensitivity of the results so far across subsets of the data. We do this in three ways. First, we investigate the sensitivity of the results to the influence of particular observations in the sample, paying close attention to the size

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[11] Of course, all results hinge upon accurate respondent recall. As previously mentioned, Elias (1991), amongst others, has studied the reliability of retrospective data. We acknowledge here that life events such as childbirth are usually associated with a high level of recall accuracy.

of the residuals and the amount of leverage associated with these observations. Second, we re-estimate some key equations across subsets of the sample defined according to educational level attained and by manual non-manual status, in order to observe whether the results hold across these sub-groups. Third, we undertake quantile regressions at different points in the earnings distribution in order to see whether there are differences in the response of wages to the work experience and other key variables at different quantiles of the wage distribution.

Leverage and Residual Outliers

Table 5.22 reports the results of three specifications with and without adjustments for the effects of outlying residuals and leverage. Individual observations lying away from the mass of sample observations are said to have high leverage if the regression line passes close to them. Were this observation not present in the data, its removal may have a large effect on the estimated regression line. Conversely, individual observations lying far away from the fitted regression line, where the predicted value of the dependent variable is far away from the actual value (so-called outlying residuals) may also exert undue influence on the estimates. The regression estimates are forced to pass closer to these observations than may be necessary.[13]

We take three specifications from the previous results, (columns I and II in Table 5.20 and column III in Table 5.21), and run them over the sub-sample without including the observations with high leverage or large studentised residuals. We use two methods of assessing the combined effect of leverage and the residuals: the Welsh and Kuh (1977) statistic and the Cook's Distance statistic (Cook (1977)). Essentially, these statistics are weighted indices representing the combined effect of the size of residuals and the size of leverage.[14] We remove those observations which exceed the values $2\sqrt{(k/n)}$ on the Welsh and Kuh (1977) measure, (where k is the number of right hand side variables, and n is the sample size) or exceed the value $4/n$, when using the Cook's Distance statistic,

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[12] European Union regulations later equalised the qualifying period to two years.

[13] For example, individuals with very high or very low hourly wages might be thought to have potentially high leverage in our sample. An individual with measurement error generating low wages, but with a lot of full-time work experience may give rise to a residual outlier in our estimates.

[14] The Welsch and Kuh statistic is $d = r_i\sqrt{(h_i/(1-h_i))}$ where r_i are the studentised residuals, dividing each residual by its appropriate standard error, $r_i = e_i / (s_i \sqrt{1-h_i})$ and h_i is the leverage measures obtained from the diagonal elements of the hat matrix $H = X(X'X)^{-1}X'$.
The Cook's Distance is then $[1/k \ (s_i^2 / s^2)] d_i^2$ where k is the number of variables, s is the root mean square error, and s_i is the root mean square error when the i^{th} observation is omitted.

as recommended by the respective authors, since these may be the observations that pose the greatest cause for concern.

Table 5.22 gives the results. We present results for all women, (columns I, III and V) and for the sub-sample not subject to excessive leverage or outliers, (columns II, IV and VI). We note that our principle variables of interest, total length of non-work spell (*outspell*) and total work experience, are affected negligibly by the removal of observations with high leverage and studentised residuals. The negative impact of non-work time is marginally reduced whilst the positive return to experience is raised slightly. The effects of different types of full and part-time work and of the different types of non-work time are also little changed. As the effects are so slight, we continue to work with the full sample in what follows.

Do the results hold across groups of women with different levels of education and occupational status?

Table 5.23 reports our three specifications estimated over two different sub-samples: that of women with low (A' level and below) and high educational qualifications.[15] There is some evidence that the returns to experience and time out do vary by education. While the estimated overall penalty to an out of work spell is similar across the two groups, the estimated returns to work experience are higher for the lower education group. This holds for the samples of all women in work in 1991 and the sub-sample of women with some career break. The penalty to part-time work is larger for those with higher qualifications, as are the penalties to unemployment. Of the other variables, it is interesting to note that the union wage premium is greater for the higher education group and that the large firm effect is greater for the low education group.

We next perform a similar exercise, by splitting the sample of women into manual and non-manual occupations. The results are reported in Table 5.24. The general pattern of results is similar to that of Table 5.23, because of the high correlation between education and occupation. Hence, the return to work experience for manual workers is higher than for non-manuals and the penalties to part-time work, unemployment and child care are

[15] Those with higher technical qualifications and degrees comprise around one third of the sample.

greater for non-manual workers. In all cases the sample split is accepted on the basis of a Chow test for equality of coefficients across the two groups.[16]

Quantile regressions

We next see whether our results hold across different groups of women, as defined by their earnings ranking in the wage distribution. To do this, we undertake quantile regression estimation: estimating the median, 25th and 75th percentile of the log hourly wage distribution conditional on the set of independent variables used in our preferred specifications highlighted above. Quantile regression finds a line through our data that minimises the sum of the absolute residuals, rather than the sum of the squared residuals.

Let q be the quantile to be estimated, $0 < q < 1$. Let the residual for each observation be

$$r_i = y_i - \sum_j \beta_j x_{ij} \qquad (5.5).$$

Let $h_i = 2q$ if $r_i > 0$ (that is, positive residuals)

$= 2(1-q)$ otherwise (negative residuals).

The quantity being minimised with respect to β_j is $\sum_i |r_i| h_i$. The quantiles other than the median are estimated by weighting the residuals. When estimating the 75th quantile regression, for example, the negative residuals are weighted by 0.5, and the positive residuals are weighted by 1.5. The useful features of quantile regressions are summarised in Buchinsky (1998). For our purposes, we wish to see whether changes in the set of explanatory variables, notably those connected with work experience, provoke a different response in the dependent variable at various quantiles of the wage distribution.

Table 5.25 reports the coefficients, standard errors and the pseudo R^2 for various quantiles[17] for the three models using the entire sample of women and the sample of women who have had a break. Here, where the standard errors are potentially

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[16] Using the Chow test, F(k, N1+N2 –2k) = [Rest. RSS – Unrest. RSS]/k / Unrest. RSS / (N1+N2 –2k), where Unrest. RSS is calculated as the sum of the RSS from the separate regressions for manual and non-manual with sample sizes N1 and N2, Rest. RSS is the RSS from the pooled regression and k is the number of right hand side variables including the constant.

[17] The pseudo R^2 we use here is 1 – [(sum of weighted deviations about the estimated quantile) / (sum of weighted deviations about the raw quantile)] .

heteroscedastic, the standard errors were obtained by the bootstrapping method using 100 replications (see Koenker and Bassett (1982)).[18]

The Table shows clearly that the returns to work experience increase as we move up the wage distribution (the coefficient on actual work experience becomes larger as we move from the 25th to the 50th to the 75th percentile). Similarly, the negative impact of time spent not in work (*outspell*) is larger, the higher up the wage distribution. This suggests that the simple splits in the preceding section into education and occupation were too crude to pick up the subtleties of the underlying data generating process. While the coefficients on full-time work are not significantly different from each other across the quantiles, the penalty to part-time work is larger at the 75th percentile. The penalty to a spell of unemployment is lower at the bottom quarter of the wage distribution, whilst at the middle and top end the effects are similar. However, the negative impact of a spell in childcare, rises as we move up the wage distribution. Note that the other control variables of interest do not change much over the quantiles.

Summary

Essentially, this Chapter focuses upon whether women with career breaks command lower wages on their return to the labour market. This Section has shown that there are significant wage penalties for time spent not in work. On average, a year spent out of work is associated with a loss of earnings of the order of 2 per cent. However, there are large variations around this average with, notably, the penalty to time out being roughly 3.5 times larger at the 75th percentile of the wage distribution than at the 25th percentile. Time out spent in unemployment carries the largest wage penalty, whereas time spent in education and training increases subsequent earnings. It is also apparent that most of the returns to work experience are found in full-time and not part-time work. The penalties to time out persist in the presence a large number of controls. It is possible, however, that these results derive from any remaining unobserved heterogeneity that is associated with earnings determination. It is to this issue that we now turn.

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[18] Given a sample of size N, the bootstrapping procedure draws a sample also of size N, but with replacement. In this case, the method runs 100 quantile regressions, calculates the standard error of the estimates for each sample, and then finally takes the average of these estimates.

5.4 Issues of Selectivity

5.4.1 Estimation Allowing for Selectivity

The last section illustrated how the effect of spending time away from continuous employment had a negative and significant effect on wages. However, if unobserved characteristics play an important part in wage determination then the negative effect that we observed may be biased, if unobserved heterogeneity is not controlled for. Given a general wage equation of the form:

$$\ln W_i = \beta_i x_i + u_i$$

$$u_i = \mu_i + \varphi_i \qquad (5.6)$$

then we may think of the error term, as consisting of two components: μ_i, the unobserved characteristics that are assumed to remain fixed over time and which may be correlated with the observable characteristics, and φ_i, a white noise error term. It is possible that some of the regressors (for example, experience, time out and job tenure) could be correlated with one or both of these error components. The literature generally deals with this by instrumentation, fixed effects or selectivity methods. Two issues arise. First, as Sections 5.2 and 5.3 suggest, non-working women may systematically differ from their working counterparts, and so our results may not generalise to the sample of women as a whole. Second, as suggested in Chapter 4, (Section 4.2), women may choose to take time out of work in accordance with some unobservable characteristic (and thereby possess less work experience). This characteristic may be correlated with some bundle of attributes that are remunerated at a low wage. That is, would this group of workers receive a low wage even if they were continuously employed? If this is so, then the inclusion of a time out dummy variable amongst the list of regressors in (5.6) may incorporate something other than merely the effects of a career break. In other words, the time out dummy variable may be endogenous. This second type of selectivity we refer to as the treatment effect. We address each of these issues sequentially, rather than attempt to model them simultaneously.[19]

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[19] See Eckstein and Wolpin (1989) for an attempt to account for these two effects simultaneously (participation and the self-selection of experience) in a dynamic, structural model of labour supply.

5.4.2 Selection Models

We begin by using the standard selectivity approach. It may be the case that the estimation process needs to be adjusted for incidental truncation of the error term. The sub-sample of working women may not be representative of the population of women as a whole. Since labour supply theory suggests individuals will participate in the labour market only if the wage offer exceeds their reservation wage, then wages are only observed for those women with a wage offer in excess of the reservation wage. So the (accepted) wage we observe is incidentally truncated. In other words, it is observed only for the sub-sample of women with an offered wage that exceeds their reservation wage.

Our approach to this issue is to view, simultaneous to the wage equation in (5.6), an associated employment equation. Let P_i^* be some unobservable index, reflecting the process whereby the decision to work is determined[20] which depends on a set of characteristics w, so that

$$P_i^* = \gamma' w_i + \varepsilon_i \tag{5.7}$$

We observe participation in work as follows

$$P_i = 1 \quad \text{if } P_i^* > 0$$
$$P_i = 0 \quad \text{otherwise} \tag{5.8}$$

that is, only if the latent variable P_i^* exceeds a given threshold which prompts women to enter work.

Given a wage equation of the form,

$$\ln W_i = \beta_i x_i + u_i \tag{5.9}$$

W_i is observed only for the sub-sample of working women, so that the error term becomes conditional on positive participation. Let the correlation coefficient between the error terms, u_i and ε_i, be ρ. That is, there are unobserved influences on the probability of a female not working, which are not controlled for in (5.8), that may have wage-depressing effects in the wage equation (5.9). To obtain a model that applies to the observations in our sample, Heckman (1979) shows that the correlation between

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[20] Hardoy (1998) refines such analysis by drawing out the distinction between selection rules and the sampling rules. Person-specific unobserved heterogeneity may bias results due to the treatment selectivity issues (which we deal with here), and also due to the rules by which individuals are sampled. We leave the extension that the latter provokes to further work.

errors results in the expected value of earnings, for the sample of working women, becoming:

$$E [\ln W_i \mid P_i = 1] = \beta' \mathbf{x}_i + E [u_i \mid P_i = 1] = \beta' \mathbf{x}_i + E [u_i \mid \varepsilon_i > -\gamma' w_i]$$

Using the rules on means of truncated bivariate normal distributions, this expression can be written as

$$= \beta' \cdot x_i + \rho\sigma_u \left[\frac{\phi(\gamma \cdot' w_i)}{\Phi(\gamma \cdot' w_i)} \right] \qquad (5.10)^{21}$$

The term $$\frac{\phi_i}{\Phi_i} = \lambda_i \qquad (5.11)$$

is the inverse Mills ratio. By estimating the model, but omitting λ_i, the coefficients in the least squares estimation are biased. The process needs to be moderated by the inclusion of λ_i.

The estimation procedure is as follows. Whether or not a female works is estimated using a standard probit model. It is desirable, though not technically necessary, to require that the probit equation contain variables that do not appear in the wage equation (the identification issue).[22] Chapter 2 shows that female participation is influenced by household composition. Female non-participation may be thought to be a function of such variables as the number and age of youngest children at home and partner's labour market status. We use these variables and the previous part-time work status variable represented in the vector w_i to identify our selection equation. The inverse Mills ratio are subsequently calculated using the predicted values from the probit over the whole sample of NCDS women. When included in the wage equation, the coefficient on this term, $\beta_\lambda = \rho\, \sigma_u$, captures the correlation between participation and the wage equation.

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[21] Note that $[\phi(\gamma'w)] / [\Phi(\gamma'w)] = [\phi(-\gamma'w)] / [1-\Phi(-\gamma'w)] = \lambda$ since the standard normal distribution is symmetric.

[22] If all the variables that appear in the probit equation also appear in the wage equation then identification proceeds on the basis that the inverse Mills ratio is a non-linear function of the variables concerned, but this is a rather tenuous foundation on which to proceed. It should also be borne in mind that selectivity estimates may be very sensitive to the choice of variables included in the probit equation.

The Treatment Effect

The second selection issue deals with the potential endogeneity of the time out (or experience) variable when included on the right hand side of the wage equation. Individuals who choose a period of home time may be essentially different to those who do not. If a woman would have commanded a low market wage whether or not she had had hometime, but is observed in our sample as having had a period outside the workforce, then the estimated coefficient on time out may overestimate the impact of a career break. This issue may be illustrated by using a simple dummy variable for home time, TO_i, as the experience-type variable in our wage equation. This cannot be treated as exogenous, if the individual herself has chosen to take such a break. Rather than deal with the issue of participation as above, the treatment model deals with the problem of a potentially endogenous dummy variable. Let T_i^* be some unobservable index, reflecting the process whereby home time is selected, which depends on a set of explanatory variables, Z_i. So,

$$T_i^* = \gamma' Z_i + \tau_i$$

and we observe a dummy variable

$$TO_i = 1 \qquad \text{if } T_i^* > 0 \qquad \text{that is, time out is taken,}$$

$$TO_i = 0 \qquad \text{otherwise} \tag{5.12}$$

Given a wage equation of the form:

$$\ln W_i = \beta_i x_i + \delta TO_i + u_i \tag{5.13}$$

if the probability of having taken hometime is correlated with τ_i there are influences on the probability of a female taking home time that also have wage-depressing effects in the wage equation (5.13). It follows that the expected value of earnings for the subset of women with time out is given by

$$E[\ln W_i \mid TO_i = 1] = \beta' x_i + \delta + E[u_i \mid TO_i = 1]$$

which, if τ_i and u_i have a bivariate standard normal distribution, is given by

$$E[\ln W_i \mid TO_i = 1] = \beta' \cdot x_i + \delta + \rho\sigma_u \left[\frac{\phi(\gamma \cdot' z_i)}{\Phi(\gamma \cdot' z_i)} \right] \tag{5.14}$$

where, as before, $\frac{\phi_i}{\Phi_i} = \lambda_i$, but now defined over the set of variables, z.

Similarly, for the subset of continuous workers,

$$E[\ln W_i \mid TO_i = 0] = \beta \cdot' x_i + \rho\sigma_u \left[\frac{-\phi(\gamma \cdot' z_i)}{1-\Phi(\gamma \cdot' z_i)} \right] \tag{5.15}$$

Notice that the difference in expected earnings for those who receive the time out treatment and those who do not is

$$E[\ln W_i \mid TO_i = 1] - E[\ln W_i \mid TO_i = 0] = \delta + \rho\sigma_u \left[\frac{\phi_i}{\Phi_i(1-\Phi_i)} \right] \tag{5.16}$$

The net result will be a different estimate of δ that will account for the self-selecting nature of time out. By estimating the model, but omitting λ_i, the difference in earnings between the two groups is exaggerated if the correlation between the error terms (τ and u), ρ, is greater than zero. In this case, the least squares procedure overestimates the negative impact of time out, TO_i. λ_i captures other wage-depressing characteristics of women not associated with the home time experience. For women with time out, labour market wages may have been lower compared to their continuous counterparts had their participation remained uninterrupted. *A priori*, we would expect the coefficient on λ_i ($\rho\sigma_u$) to be positive and significant, given that some women select periods of home time through voluntary choice.

The estimation procedure of the model is as follows. Whether or not a female has had time out is estimated using the standard Probit Model. The inverse Mills ratio are subsequently calculated using the predicted values from the probit on the sample of NCDS women in work, (not on all women in the sample, as with the standard selection model). Again the results may depend on which variables are included in the selection equation but not the wage equation. We use the same set of identifiers, age of youngest child, previous part-time work status and partner's labour market status, as in the standard selection probits to identify the probability of having taken time out. These variables do not enter the associated wage equation.

Instrumenting Dummy Endogenous Variables

Bowden and Turkington (1990),[23] show that the problem of an endogenous explanatory dummy variable can also be addressed using an instrumental variable approach. Rather than include a selection correction term in the wage equation, they suggest that the endogenous dummy variable can be instrumented directly. Given a set of exogenous variables, w_i, that explain time out (but not wages), then define an instrument,

$$\begin{aligned} \tilde{TO}_i &= 1 \quad \text{if individual } i \text{ is predicted to have had time out} \\ &= 0 \quad \text{otherwise} \end{aligned} \tag{5.17}$$

The predictions are based on a probit equation of time out on the set of exogenous variables, w_i . Note that this is the same probit equation as appears in the first stage of the treatment selection model. If the predicted probability of having had time out in the past is greater than or equal to 0.5, we assign the individual to the $\tilde{TO}_i = 1_i$ category. If the predicted probability is less than 0.5, the individual is assigned to the $\tilde{TO}_i = 0_i$ category. This variable is then included as an instrument for TO_i in the wage equation.[24]

Results

Table 5.26 reports the Heckman selectivity corrected wage equations, where the selection controls for the participation of women in work. The initial probit specification (column I) shows that the probability of being observed in employment is positively related to post-compulsory education and marital status, and inversely related to the number of children. A history of part-time work is positively associated with being in work in 1991. In Table 5.26, we report three specifications of the wage equation, reflecting the key findings of the previous section. Our selectivity adjusted wage equations in this table (columns II, III and IV) should be compared with those of Table 5.17 (column III), Table 5.19 (column III) and Table 5.21 (column III). These 3 equations contain, respectively, actual experience and its square, actual experience split

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[23] Bowden and Turkington (1990) pages 42-44.

[24] While instrumental variable estimates may be consistent, they may still be biased in finite samples. Further, such estimates may be inefficient if the instruments are only slightly correlated with the endogenous variable. (See Bowden and Turkington (1990) and also Johnson and DiNardo (1997).) Greene (1993) points out that the choice of 0.5 as a threshold is arbitrary. We experimented with different thresholds and the estimated coefficient on instrumented Time Out varied from around -.04 to -.06.

into its pre- and post-gap components and actual experience and time out split into its constituent components. In none of the specifications is the selectivity term (λ) significant and, as a result, the coefficient on the variables of interest (education and experience) are largely unchanged.[25]

Table 5.27 reports the results of the treatment model, where the selection now takes place on the time out dummy right hand side variable. Column I reports the probit on the probability of having had time out, column II gives the results of a wage equation containing a time out dummy, and no other experience controls, column III repeats the specification including an inverse Mill's ratio (λ). Column IV gives wage equation estimates where Time Out is instrumented following the procedure outlined earlier. As with the previous selection on participation equation, the probability of having had time out is positively correlated with higher levels of education, with the number of children and with a history of part-time work. The unadjusted coefficient on the time out dummy suggests that having had time out is associated with earnings 6.6 log points lower than those without time out. The introduction of a selectivity term reduces this a little, such that the time out penalty is now associated with earnings that are 5.8 log points lower. The instrumented estimate of Time Out in column IV is also lower, at around 4.2 log points, and no longer significant.[26] Together, these results suggest that there may be a small endogeneity effect, whereby women who have time out would have earned lower wages even had they had continuous work histories. We refrain from drawing too strong a conclusion, however, until a satisfactory set of instruments can be found.

Extension to Multiple Selection Outcomes

Following Lee (1983), the selectivity approach can be extended to the case where there are more than two outcomes. As recognised by Groot and van Ours (1994), the selectivity problem may not be confined to the simple observation of whether or not women are in work; or confined to one potentially endogenous dummy variable. Women may be employed having never had an interruption, may be back in work following a break (with or without passing a probationary period) or they may not be in

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[25] These results are sensitive to the choice of identifier. We tried various specifications of the probit model, but the results were little changed.

[26] An increase in the estimated standard error is a common feature of instrumentation.

work at all. Allocation across these labour market states is not likely to be random. Any attempts to estimate rebound effects or the returns to work experience may suffer from selectivity bias, as the resulting groups may be a self-selected sample.

The extension from the two variable case to the case where there are more than two options is relatively simple. This new approach is similar to the two step Heckman (1978) method for endogenous dummy variables. The probit selection equation is replaced by a multinomial logit estimation routine. The equation essentially estimates the probabilities of being in the different labour force categories.

Let $I_{ij} = 1$ if the i^{th} woman is observed in labour force category j. Otherwise $I_{ij} = 0$ ($j = 1, \ldots, n$) where n reflects the total number of labour force status categories included. The worker will only be observed in labour force category j if the index

$$V_i\alpha_j + \varepsilon_i > \max(\Sigma_k V_i \alpha_k + \varepsilon_{ik}, 0) \text{ for } i \neq k, \quad i, k = 1, \ldots, n \tag{5.18}$$

where V is a vector of characteristics determining the labour force status of the individual, with associated coefficients α, and ε_i is a random term capturing unmeasured determinants on labour force categories. Assuming ε_i has a logistic distribution generates the multinomial logit model.

Following Lee (1983) the multinomial logit distributions are transformed to standard normal random variables and the selectivity bias correction term for category j (that is, Λ_{ij}) becomes

$$\Lambda_{ij} = I_{ij}\,\lambda_{ij} - (1 - I_{ij})\lambda_{ij}[(1 - F(V_i\alpha_j))/F(V_i\alpha_j)] \tag{5.19}$$

where $\lambda_{ij} = \phi(J(V_i\alpha_j))/F(V_i\alpha_j)$. $F(V_i\alpha_j)$ is Prob$(I_{ij} = 1)$ in the multinomial logit distribution and $J(V_i\alpha_j) = \Phi^{-1}(F(V_i\alpha_j))$ which converts the estimated multinomial logit probability into a value on the cumulative standard normal distribution function abscissa. These correction terms are then added to the wage equation, so that we estimate

$$\text{Ln wage}_i = \beta_0 + \beta_1 S_i + \beta_2 X_i + \beta_3 X_i^2 + \gamma Z + \omega_1\Lambda_{i1} + \omega_2\Lambda_{i2} + \ldots + \omega_n\Lambda_{in} + u_i \tag{5.20}$$

The coefficients on the ω_i are the covariances between $J(V_i \alpha_j)$ and u_i. Negativity of the ω_i coefficients indicates that the lower the reservation wage becomes, the higher the probability that a worker will find a job. Positivity of ω_i suggests that an individual who is out of work may have a positive probability of receiving offers of employment.

The results of the multinomial logit selection equations are given in Table 5.28 (a) and (b). We report two selection equations. The first uses four labour force states: continuous employment, work returners with current tenure less than the assumed rebound period of 24 months, work returners with current tenure 24 months (or above), and those not in work. To allow for the possibility, as revealed by earlier results, that the various out of work states may have different effects on the rebound, we use a second selection equation (Table 5.28(b)). This splits work returners into those who have had a break in home production and all other out spell categories: creating 6 labour force states in total.[27] The default category in both cases is the set of those women not in work. We follow Groot and van Ours in our multinomial logit selection equations by including regional, marital status, young child and education dummies and a continuous variable for the years of education. Obviously, identification of the wage equation relies heavily on non-linearity in the selection terms. Since, we believe that there are few variables which truly influence participation and not wages, then the introduction of selectivity correction terms, which are effectively non-linear combinations of existing variables, $(\lambda_{ij} = \phi(J(V_i \alpha_j)) / F(V_i \alpha_j))$ in the wage equation, are sufficient to identify the model.

Table 5.28 (a) shows that women with the technical educational attainment are more likely to have been in work continuously and that women with young children are significantly less likely to have been in continuous employment. Table 5.28 (b) reveals that women with young children are relatively more likely to have spent time at home (rather than any of the other non-work groups) before returning to work (compare column II with columns III, IV and V for the young child dummy).

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[27] Small sample sizes prevented us from splitting the returners into previously unemployed, in training and so on for the multinomial logit.

Columns II and IV of Table 5.29 give the selectivity adjusted estimates of rebound effects in the wage equation, using the estimates from Tables 5.28(a) and (b) respectively to calculate the selection terms. The unadjusted estimates are given in columns I and III. Column II is the estimate of Equation (5.20), where work experience is divided into that attained before the last break, the rebound period after the last break, (set to 2 years) and residual tenure (if back in work for greater than 2 years). These variables appear alongside a measure of the length of the last break.

The results suggest that work experience before the last break adds little to current earnings and that the 2 year rebound period is insufficient to offset the negative impact of a break in employment of more than nine months (compare the coefficient of -.020 points a year for time out with the coefficient of .007 a year for rebound). Thereafter, further experience in the job will work to offset these time out effects. The selectivity controls in column II, however, reduce, but do not remove, the penalty to time out, (as with the earlier treatment model), and strengthen the impact of the rebound effect relative to current tenure. The rebound coefficient is now positive, significant and larger than the coefficient on job tenure suggesting that all the loss from a break is offset within the rebound period, once self-selection is controlled for.

Column III splits both the duration of the last break and the rebound effect according to whether the break was spent in childcare, unemployment, education or some other category. As before, the wage penalty to unemployment is significantly larger than the penalty to childcare, which in turn is larger than the effect of having had a break in education. Childcare (home time) continues to have a negative effect on pay even after allowing for selectivity effects The rebound effects on education and the *other*, unspecified, category are much larger than the rebound effects on childcare and unemployment (if anything, the latter are negative). In the absence of controls for selectivity, earnings restoration after having had a break spent in childcare or unemployment occurs after the end of the two-year rebound period. However, following the inclusion of the selectivity controls in column IV, the magnitude of all the rebound coefficients are increased again. The rebound coefficients on unemployment and home time are no longer negative, but are insignificantly different from zero. For a spell in childcare, the coefficients suggest that the wage effect of a one-year break will

be offset following one year spent back in work. For a one-year spell in unemployment, this effect will be achieved after two years. The rebound effect is larger for women with unemployment, but the penalty to time out of work for women with unemployment is also larger compared to women with child care. Thus the overall penalty is larger for women with a spell of unemployment. The selectivity terms confirm that there is positive association between continuous work and wages and that wages for those women back in work for more than two years are larger than for more recent returners. However, in the absence of an appropriate identifier, we merely note that including selection terms has the expected effect on experience and we leave the search for better instruments to future work.

5.5 First Difference Estimation

The preceding section attempts to control for the effects associated with women selecting themselves into periods of non-paid work. The unobserved differences between workers which lead them to take career breaks may play a key role in explaining the wage penalty between continuous and intermittent workers. Unequivocally, there exist differences between groups of women that cannot be accounted for by differences in human capital endowments. An alternative way of dealing with these unobserved effects (such as motivation) is to assume that they do not vary over time. By working with a first difference specification in the earnings equation, any fixed effects are removed. Waldfogel (1993) attempts to control for various unobservable characteristics that may be linked to the higher earning power of some women (characteristics such as ability and drive) in this way. Waldfogel's evidence suggests that there is not much support for the view that being a working woman and having children and gaining a lower wage is correlated with unobserved heterogeneity and lower earnings ability. We test to see whether this procedure affects the estimates of different types of non-work spell. It may be that when we control for fixed effects, the intermittent workers who have children constitute that sub-sample of women who have lower earnings. That is, if the source of the endogeneity is with the individual-specific component of the error term, then fixed effects estimation will provide consistent estimates of the model. So in this Section, to control for unobserved heterogeneity, we use a first difference specification. This seeks to estimate the effect of

changes in the individual regressors on the difference between two log wage observations:[28]

$$\Delta \ln W_i = \Delta e_{0i} + \Delta e_{0i}^2 + \Delta h_{0i} + \Delta V_i + \Delta \mu_i + \Delta \varphi_i \qquad (5.21)$$

where all variables are defined as above. The change, $\Delta ln\ W_i = (ln\ wage_{\ i\ 1991} - ln\ wage_{\ i\ 1981})$, represents the difference between the Sweep 5 wage and the last observed Sweep 4 wage for each individual. The disturbance term φ_i is assumed to be independent and identically distributed, with zero mean and variance σ^2. The fixed effect is captured in the μ_i term. By working with the first difference specification, the term $\Delta\mu_i$ is zero and the fixed effect disappears. Now V contains only those characteristics that change between wage observations (namely, the number and age of children, marital status, the amount of work experience and its constituent parts, and the amounts of non-work experience). All variables in difference form, therefore, represent the change between the sample observations between 1981 and 1991. For example, the work experience term in differences represents the change in the amounts of work experience from 1981 to 1991, and similarly the difference in the *outspell* variable the change between these two dates for the total amount of non-work time. Workers reporting wages in both sweeps (with no missing or inaccurate job histories) are included in this sample.[29] This reduces our sample size from that of the previous section. We therefore repeat the key regressions in levels form for wages at Sweep 5 on the new sample alongside the difference estimates. Waldfogel (1993) follows a similar procedure, but she enlarges her sample of women by including the range of all possible wage observations. That is, where information on the wage in 1991 was missing, she uses the last known wage (the wage from the preceding job). This is not what we do here, as it is impossible to pinpoint the exact date of the wage observations other than those collected at the interview date for Sweeps 4 and 5.[30] The absence of dates makes it impossible to calculate precisely the relevant amount of work experience for the wage from the

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[28]Our sample restricted to observations that include at least two wage observations may also be biased by selection effects. Following Waldfogel (1993), we do not seek to address this potential source of bias in this section.

[29] Fixed effects estimation will exacerbate any problems caused by measurement error in the experience variable generated by retrospective recall bias. Any error in the levels is made worse by the difference process. This may therefore downward bias the estimated coefficients.

[30] The NCDS includes wage information on the cohort member's current job, the last job (where the current job does not exist), and the second from last job. In this section, we use information specifically on the current job, in case those women not in work at the interview date in 1981 and 1991 are systematically different from those in work on these dates.

preceding job. The first difference procedure eliminates from the regression any characteristic that is invariant for a worker over our ten year window. Thus, regressors, such as educational attainment and region, which are fixed over time for each individual, drop out of the difference analysis, but appear in the wage equation.[31]

Table 5.30 outlines the change in average wages, work experience and length of outspell between 1981 and 1991. The average growth in real hourly wages over the period is around 30 log points, which disguises much larger wage growth differences between manuals and non-manuals. Manual workers have the largest amount of work experience in 1981 consistent with this group having left full-time education earlier. Not surprisingly, the total amounts of in and out of work experience rise between the two dates. The rise in work experience for non-manuals was higher than for manuals, whilst the rise in non-work experience was higher for manuals. Childcare accounts for around half the increase in time out of work, and around three quarters of the increase for manual workers.

Table 5.31 reports Ordinary Least Squares results of first differences for three alternative specifications, alongside level estimates for wages in Sweep 5.[32] The Table shows that the coefficient on actual work experience is increased when moving from the levels to the first difference results by around 1.8 percentage points (compare columns I and II). The *any kids* variable demonstrates the effect of changing family size from having no children to having one or more children in the difference specification. Similarly, *married* captures the effect of going from the single to the married category within our ten-year window. Controlling for unobserved heterogeneity has a small effect on the estimated effects of these variables. When experience is split into its full- and part-time components, the negative effect of part-time work is much reduced in the first difference specification (see columns III and IV). This suggests that unobservable characteristics may be negatively linked to wages and part-time work. The differenced estimates for the type of break specification (column VI) are smaller than the levels

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[31] The variable on VDU use does not appear in Sweep 4.

[32] Waldfogel (1993), uses a similar technique but does not distinguish between the nature of the time out spell. Her variable "hometime" includes all time unemployed or out of the labour force (Waldfogel (1993), page 18). We are explicitly interested in the comparison of effects of periods spent in home production against other forms of withdrawal.

(column V). The negative effect of home time is reduced by more than half in the differenced model, but remains significant. Now, the overall home time effect can no longer distinguished from the unemployment effect. So, on this basis, there remains a wage penalty to childcare even allowing for unobserved heterogeneity, of around 5 per cent a year. Notice that this may be a lower bound on the time out effect if the reservations regarding the consequence of the differencing process raised in footnote 21 hold, since measurement error biases down estimated coefficients. The (positive) effect of education on subsequent earnings rises under the first difference specification although it is no longer significant. The negative effect of unemployment is relatively unchanged by differencing.

The results obtained on the childcare variable complement those found above in Table 5.29, where the controls for self-selection reduced the penalty to time spent in childcare. This suggests that there may be some unobserved heterogeneity correlated with childcare that upwardly biases the estimates of the penalty to time out spent in childcare. These effects do not appear to be present for a spell of unemployment and are obscured when a general measure of time out (rather than the specific type of time out) is used. However, the negative penalty, whilst reduced, is still persistent.

5.6 Conclusion

We set out to investigate the effect of breaks in continuous employment on earnings. This Chapter has presented new evidence on the effect of work interruptions on earnings for Britain. The nature of the data set we employ allows us to undertake a study where actual experience, both in and out of work, are used as explanatory variables in a wage equation, rather than the usual proxy of potential experience. This has facilitated a detailed study of the effects of experience on earnings. Our results indicate that use of potential experience may seriously overestimate the returns to work experience in earnings equations.

We explore whether women who have a spell out of work receive lower earnings as a result. We find that time out of work does have a negative effect on re-entry wages. Women who take time out experience lower earnings than those who work continuously. The average earnings loss is around 1 to 2 percentage points a year. The

size of this penalty is similar to Mincer and Ofek's (1982) results for the United States. Having established that there are lower earnings for those with time out, we then tried to establish whether this could be attributed to differences in the characteristics, both observed and unobserved, of women who work continuously and women who do not. The wage difference is indeed robust to the inclusion of a large set of controls for observed heterogeneity afforded by the NCDS data set. The overall wage difference is reduced, but persists, when we attempt to control for unobserved individual heterogeneity using selectivity and first differencing methods.

The size of the earnings penalty varies with the type of out of work spell. Those who are unemployed suffer the highest earnings penalty (at around 7 per cent for each year out), but there is still a significant negative impact on earnings for a spell of childcare (at around 4 to 5 per cent for each year out). Again, this childcare penalty is reduced, but does not disappear, when unobserved heterogeneity is controlled for. Whilst the characteristics of women who take childcare may lend themselves to lower earnings there still appears to be more underlying processes at work which may be caused by the depreciation of human capital during time out or due to the signalling effect of time out. There is evidence that women who return to work may make up some of their lost earnings, but this is quicker for those who are out for reasons other than unemployment or home production. This is consistent with the Mincer and Ofek (1982) view of the existence of a human capital restoration period: but only for specific types of time out. The stylised single-peaked lifetime earnings profile is inappropriate in the context of female intermittent workers and the work above provides conclusive evidence for this. Moreover, it is the case that a history of part-time work is associated with much lower hourly earnings than those of women who pursue a career in full-time work. Wages mostly accrue, in our data set, to women with experience of full-time work. This may explain why we observe larger experience effects on earnings as we move up higher quantiles of the wage distribution. These findings also have important implications for helping to explain the different wage experiences of men and women. Chapter 6 goes on to investigate the link between time spent out of work and the gender wage gap in more detail.

Table 5.1 Summary of Work History Patterns by Age 33

Number of Jobs since School	*Total*	*Married*	*Lone Mothers*	*Single*	*Married with children*
	Frequency (%)	Frequency (%)	Frequency (%)	Frequency (%)	Frequency (%)
All women					
0	1.0	0.7	1.2	2.0	1.3
1	12.3	13.7	8.0	12.4	13.3
2	14.6	15.2	13.6	13.3	15.6
3	17.8	18.6	16.8	15.8	18.5
4	16.3	16.8	17.1	13.6	17.4
5	12.6	12.2	13.7	12.6	12.4
6	8.4	8.1	9.5	8.1	7.8
7	5.7	5.3	5.5	7.3	5.1
8 +	11.3	9.4	14.6	14.9	9.2
Mean number of jobs	4.2	4.0	4.6	4.5	4.0
Working women					
1	10.4	11.3	4.5	13.4	9.8
2	13.3	13.5	12.0	13.8	13.7
3	17.9	18.6	16.7	16.3	18.3
4	16.8	17.9	16.8	13.8	19.0
5	13.1	12.5	14.3	13.4	13.3
6	9.8	9.6	11.6	8.7	9.4
7	6.2	5.8	6.5	7.1	5.5
8 +	12.5	10.9	17.6	13.6	11.1
Mean number of jobs	4.5	4.3	5.1	4.5	4.3

Note: Sample 1. All Women in 1991 N=6857 Sample 2. Women in work in 1991 N= 4712

Table 5.2 Summary of Work History Patterns for Working Women in 1991

	Mean Duration (years)						
Number of non-work spells	Frequency (%)	Total work	Pre-last break work	Non-work spell	Post-last break work	Total Full-time	Total Part-time
	I	**II**	**III**	**IV**	**V**	**VI**	**VII**
0	37.9	14.4 (3.6)	NA	NA	NA	12.3 (5.4)	2.1 (4.0)
1	32.6	12.1 (3.5)	5.2 (4.4)	3.4 (3.4)	6.9 (4.6)	9.4 (4.8)	2.7 (3.6)
2	17.7	11.4 (3.4)	6.2 (4.4)	4.3 (3.2)	5.2 (4.2)	8.5 (4.3)	2.8 (3.1)
3 +	11.7	10.7 (3.2)	6.4 (3.8)	5.3 (3.0)	4.3 (3.5)	7.7 (4.0)	3.0 (3.4)

Note 1. Standard deviations in parentheses 2. Sample: All Women in work in 1991, N=4712
3. NA = Not Applicable

Table 5.3 Summary of Work History Patterns for Non-Working Women in 1991

	Mean Duration (years)						
Number of non-work spells	Frequency (%)	Total work	Pre-last break work	Non-work spell	Post-last break work	Total Full-time	Total Part-time
	I	**II**	**III**	**IV**	**V**	**VI**	**VII**
Never worked	2.0	NA	NA	15.7 (2.5)	NA	NA	NA
1	44.4	8.3 (4.7)	6.7 (4.8)	6.4 (4.7)	1.5 (2.8)	7.0 (4.7)	1.3 (2.7)
2	28.0	8.7 (4.0)	7.6 (4.3)	6.9 (4.2)	1.0 (2.3)	7.0 (4.0)	1.6 (2.5)
3 +	25.6	8.0 (3.7)	7.5 (3.7)	7.3 (3.7)	0.4 (1.4)	6.2 (3.7)	1.9 (2.5)

Note 1. Standard deviation in parentheses 2. Sample: Women not in work in 1991, N=2145
3. NA = Not Applicable

Table 5.4 Summary of Non-Work History Patterns for Working Women in 1991

	Mean Duration (years)				
Number of non-work spells	Total Non-work	Home time	Unemployed	Education	Other
	I	**II**	**III**	**IV**	**V**
Total	2.5	1.6	0.3	0.5	0.2
	(3.3)	(3.0)	(0.9)	(1.4)	(0.9)
1	3.4	2.3	0.3	0.6	0.2
	(3.4)	(3.5)	(1.1)	(1.5)	(0.9)
2	4.3	2.9	0.4	0.8	0.2
	(3.2)	(3.4)	(1.1)	(1.5)	(1.3)
3 +	5.3	2.7	0.8	1.3	0.5
	(3.0)	(3.5)	(1.4)	(2.2)	(1.2)

Note 1. Standard deviation in parentheses 2. Sample: Women in work in 1991, N=4712

Table 5.5 Summary of Non-Work History Patterns for Women Not Working in 1991

	Mean Duration (years)				
Number of non-work spells	Total Non-work	Home time	Unemployed	Education	Other
	I	**II**	**III**	**IV**	**V**
Total	8.7	6.8	0.7	0.4	0.8
	(4.7)	(5.2)	(2.3)	(1.2)	(2.7)
1	6.4	5.4	0.3	0.2	0.4
	(4.7)	(4.9)	(1.5)	(0.8)	(1.9)
2	6.9	5.5	0.5	0.5	0.4
	(4.2)	(4.4)	(1.6)	(1.3)	(1.6)
3 +	7.3	4.5	1.2	0.9	0.7
	(3.7)	(3.9)	(2.1)	(1.5)	(1.9)

Note 1. Standard deviation in parentheses 2. Sample: Women not in-work in 1991, N=2145

Table 5.6 Summary of Work History Patterns for Single Working Women

	Mean Duration (years)						
Number of non-work spells	Frequency (%)	Total work	Pre-last break work spell	Non-work spell	Post last break spell	Total Full-time	Total Part-time
	I	**II**	**III**	**IV**	**V**	**VI**	**VII**
0	47.9	14.0 (3.9)	NA	NA	NA	12.4 (5.1)	1.6 (3.5)
1	28.0	12.6 (3.9)	1.2 (2.9)	2.5 (3.3)	1.1 (2.5)	10.6 (5.1)	2.0 (3.7)
2	13.4	11.6 (3.4)	1.9 (3.2)	4.1 (3.3)	1.6 (2.6)	9.0 (4.6)	2.6 (3.3)
3 +	10.6	10.6 (3.3)	2.2 (3.6)	5.5 (3.0)	1.1 (2.4)	8.1 (3.6)	2.4 (3.8)

Note 1. Standard deviation in parentheses 2. Sample: Women in work in 1991 who are single, N=968

Table 5.7 Summary of Work History Patterns for Married Working Women

	Mean Duration (years)						
Number of non-work spells	Frequency (%)	Total work	Pre last break work spell	Non-work spell	Post last break work spell	Total Full-time	Total Part-time
	I	**II**	**III**	**IV**	**V**	**VI**	**VII**
0	36.3	14.6 (3.3)	NA	NA	NA	12.3 (5.6)	2.4 (4.3)
1	33.9	11.9 (3.4)	5.0 (4.2)	3.7 (3.4)	6.8 (4.6)	8.8 (4.7)	3.0 (3.7)
2	18.9	11.3 (3.3)	6.5 (4.3)	4.5 (3.2)	4.8 (4.0)	8.3 (4.1)	3.0 (3.0)
3 +	10.8	10.8 (3.2)	6.6 (3.8)	5.1 (3.0)	4.3 (3.5)	7.2 (4.0)	3.6 (3.5)

Note 1. Standard deviations in parentheses 2. Sample: Women in work in 1991 who are married, N=2958

Table 5.8 Summary of Work History Patterns for Working Lone Mothers

	Mean Duration (years)						
Number of non-work spells	Frequency (%)	Total work	Pre last break work spell	Non-work spell	Post last break work spell	Total Full-time	Total Part-time
	I	**II**	**III**	**IV**	**V**	**VI**	**VII**
0	34.0	12.8 (4.7)	NA	NA	NA	9.9 (5.8)	2.8 (4.0)
1	32.4	11.6 (4.1)	6.3 (4.5)	4.0 (3.7)	5.4 (4.1)	8.3 (4.8)	3.3 (3.8)
2	17.4	10.6 (3.8)	6.4 (3.9)	5.4 (3.5)	4.4 (3.5)	7.2 (4.1)	3.4 (3.5)
3 +	16.3	10.1 (3.5)	6.8 (3.7)	6.3 (3.1)	3.4 (3.4)	7.1 (3.9)	3.1 (3.4)

Note 1. Standard deviation in parentheses 2. Sample: Women in work in 1991 who are lone mothers, N=847

Table 5.9 Summary of Work History Patterns for Working Married Mothers with Children

	Mean Duration (years)						
Number of non-work spells	Frequency (%)	Total work	Pre last break work spell	Non-work spell	Post last break work spell	Total Full-time	Total Part-time
	I	**II**	**III**	**IV**	**V**	**VI**	**VII**
0	32.4	14.2 (3.7)	NA	NA	NA	11.3 (5.9)	2.9 (4.6)
1	36.2	11.6 (3.5)	5.3 (4.0)	4.0 (3.5)	6.4 (4.5)	8.1 (4.7)	3.5 (3.7)
2	20.7	11.2 (3.4)	6.9 (4.1)	4.8 (3.3)	4.2 (3.6)	7.7 (3.9)	3.3 (3.0)
3 +	10.7	10.6 (3.3)	6.8 (3.6)	5.5 (3.1)	3.8 (3.3)	6.6 (3.8)	4.0 (3.6)

Note 1. Standard deviations in parentheses 2. Sample: Women in work in 1991 who are both married and who have children, N= 2307

Table 5.10.a. Summary of Work History Patterns for Working Women by Part-time Status

	Mean Duration (years)						
Number of non-work spells	Frequency (%)	Total work (years)	Pre last break work (years)	Non-work spell (years)	Post last break Work (years)	Full-time (years)	Part-time (years)
	I	**II**	**III**	**IV**	**V**	**VI**	**VII**
Women working Part-time							
0	24.0	12.1 (4.6)	NA	NA	NA	6.7 (5.4)	5.4 (5.1)
1	38.1	11.1 (3.7)	6.4 (4.6)	4.6 (3.6)	4.8 (3.9)	6.7 (4.1)	4.4 (3.7)
2	23.2	10.7 (3.5)	6.3 (3.9)	5.3 (3.4)	3.3 (2.9)	6.7 (3.7)	4.1 (3.0)
3 +	14.7	10.0 (3.5)	7.5 (3.9)	6.4 (3.1)	2.7 (2.4)	5.5 (3.4)	4.5 (3.4)
N	1775						
Women working Full-time							
0	47.3	15.0 (2.9)	NA	NA	NA	13.8 (4.3)	1.2 (3.1)
1	28.7	12.8 (3.3)	4.3 (4.6)	2.5 (2.9)	8.5 (4.5)	11.4 (4.3)	1.4 (2.9)
2	13.9	12.0 (3.2)	5.0 (4.4)	3.4 (2.8)	7.0 (4.3)	10.3 (4.0)	1.7 (2.7)
3 +	9.9	11.2 (2.8)	5.6 (3.8)	4.4 (2.7)	5.6 (3.8)	9.5 (3.4)	1.8 (2.9)
N	4506						

Note: 1. Standard deviations in parentheses 2. Sample: Women in part-time work in 1991; b Women in full-time work in 1991

Table 5.10.b. Full-Time and Part-Time Work Experience Patterns

	Mean Duration (years)							
Number of non-work spells	Total Full-time	Total Part-time	Pre-last break Full-time	Pre-last break Part-time	Post-last break Full-time	Post-last break Part-time	Non-work spell	N
	I	**II**	**III**	**IV**	**V**	**VI**	**VII**	**VIII**
In Work in 1991								
0	12.3 (5.4)	2.1 (4.0)	12.3 (5.4)	2.1 (4.0)	0	0	0	1832
1	9.4 (4.8)	2.8 (3.6)	4.7 (4.4)	0.7 (1.9)	4.7 (5.3)	2.2 (3.2)	2.4 (3.4)	1564
2	8.5 (4.2)	2.8 (3.1)	5.3 (4.2)	1.0 (1.8)	3.3 (4.5)	1.9 (2.4)	4.3 (3.2)	834
3 +	7.7 (4.0)	3.0 (3.4)	5.0 (3.5)	1.5 (2.3)	2.7 (3.7)	1.5 (2.2)	5.3 (3.0)	547
Not in Work in 1991								
1	7.3 (4.6)	1.3 (2.8)	6.8 (4.6)	1.0 (2.5)	0.5 (2.1)	0.4 (1.6)	6.3 (4.7)	900
2	7.1 (4.0)	1.6 (2.5)	6.8 (4.1)	1.3 (2.3)	0.3 (1.6)	0.3 (1.2)	6.9 (4.2)	582
3 +	6.2 (3.7)	1.9 (2.5)	6.1 (3.7)	1.7 (2.4)	0.1 (0.7)	0.2 (0.9)	7.3 (3.7)	536

Note 1. Standard deviations in parentheses

Table 5.11 Weekly and Hourly Wages by Length of Time Out

	No Break	*0 - 2 years*	*2 - 4 years*	*4 + years*
All women in work, 1991				
Mean weekly wage	296.9	256.4	234.5	155.7
	(416.7)	(394.9)	(322.9)	(291.3)
Mean hourly wage	7.8	7.2	7.0	5.3
	(9.8)	(9.7)	(8.2)	(7.1)
N	1809	993	665	1246
Part-Time in 1991				
Mean weekly wage	89.7	88.2	79.9	69.9
	(137.5)	(48.1)	(49.6)	(60.5)
Mean hourly wage	4.9	5.0	4.7	4.1
	(4.6)	(2.3)	(2.4)	(2.8)
N	394	290	254	745
Full time in 1991				
Mean weekly wage	354.6	325.7	330.1	282.2
	(448.8)	(450.5)	(378.7)	(422.6)
Mean hourly wage	8.6	8.2	8.5	7.2
	(10.7)	(11.4)	(9.9)	(10.4)
N	1415	703	411	501

Note. Standard deviations in parentheses

Table 5.12 Weekly and Hourly Wage by Number of Spells Not in Work

	No Break	*1 spell*	*2 spells*	*3 + spells*
All women in work, 1991				
Mean weekly wage	296.9	209.2	198.1	221.4
	(416.7)	(299.6)	(344.3)	(436.1)
Mean hourly wage	7.8	6.3	6.3	6.6
	(9.8)	(7.1)	(9.3)	(10.4)
N	1809	1542	810	534
Part time in 1991				
Mean weekly wage	89.7	76.2	76.7	73.1
	(137.5)	(60.0)	(52.5)	(52.4)
Mean hourly wage	4.9	4.4	4.4	4.3
	(4.6)	(2.9)	(2.3)	(2.7)
N	394	659	388	235
Full time in 1991				
Mean weekly wage	354.6	308.4	309.7	337.9
	(448.8)	(361.9)	(446.3)	(554.1)
Mean hourly wage	8.6	7.8	8.1	8.5
	(10.7)	(8.8)	(12.4)	(13.3)
N	1415	883	422	299

Note. Standard deviations in parentheses

Table 5.13 Weekly and Hourly Wage by Length of Time Since Last Break

	No Break	*0 - 2 years*	*2 - 4 years*	*4 - 6 years*	*6 years +*
	I	II	III	IV	V
All women in work, 1991					
Mean weekly wage	296.9	139.1	148.7	161.1	285.7
	(416.7)	(279.7	(256.3)	(292.6)	(394.9)
Mean hourly wage	7.8	5.1	5.3	5.6	7.8
	(9.8)	(7.5)	(6.0)	(8.2)	(9.5)
N	1809	657	495	434	1288
Part-Time in 1991					
Mean weekly wage	89.7	64.8	76.7	78.0	91.8
	(137.5)	(42.6)	(76.2)	(46.6)	(54.5)
Mean hourly wage	4.9	4.0	4.5	4.4	5.0
	(4.6)	(2.0)	(3.6)	(2.4)	(2.5)
N	394	398	307	283	284
Full-Time in 1991					
Mean weekly wage	354.6	276.1	259.5	261.1	345.4
	(448.8)	(436.7)	(371.5)	(410.1)	(433.5)
Mean hourly wage	8.6	7.1	6.6	6.9	8.7
	(10.7)	(12.1)	(8.3)	(11.8)	(10.6)
N	1415	231	195	197	985

Note. Standard deviations in parentheses

Table 5.14 Weekly and Hourly Wage by Length of Time Since Last Childcare Break

	No Break	*0 - 2 years*	*2 - 4 years*	*4 - 6 years*	*6 years +*
All women in work, 1991					
Mean weekly wage	296.9	80.7	97.2	124.1	135.6
	(416.7)	(69.8)	(91.5)	(257.9)	(86.7)
Mean hourly wage	7.8	4.1	4.6	5.1	4.6
	(9.8)	(2.3)	(3.5)	(8.5)	(1.8)
Part-Time in 1991					
Mean weekly wage	89.7	61.5	73.7	76.8	75.8
	(137.5)	(41.6)	(77.7)	(44.9)	(39.6)
Mean hourly wage	4.9	3.9	4.4	4.5	4.1
	(4.6)	(2.1)	(3.8)	(2.6)	(1.6)
Full-Time in 1991					
Mean weekly wage	354.6	177.1	188.4	228.7	197.2
	(448.8)	(98.2)	(83.9)	(441.7)	(78.6)
Mean hourly wage	8.6	5.2	4.6	6.6	5.2
	(10.7)	(2.9)	(1.9)	(14.8)	(1.8)

Note. Standard deviations in parentheses

Table 5.15 Sample Means of Key Variables

	All women		*Women with Home time*	
	Mean	S. dev.	Mean	S. dev.
Weekly wage	242.0	370.4	106.0	143.0
Hourly wage	6.95	8.99	4.56	4.66
Hours	32.0	13.5	22.2	11.3
Log Hourly wage	1.7	.57	1.3	.43
Job Tenure	5.3	5.1	2.5	2.5
Degree	.23	.42	.14	.35
Technical	.37	.48	.33	.47
A level	.01	.09	.01	.08
O level	.19	.39	.24	.43
Lower Quals.	.09	.28	.11	.31
Actual Experience	12.9	3.5	10.7	3.3
Potential Experience	15.8	1.8	12.9	70.4
Pre gap Experience	11.7	4.7	6.8	3.5
Post gap Experience	3.7	4.5	3.9	2.9
Last non-work spell	1.6	2.6	4.1	3.3
North	.04	.19	.03	.19
North West	.07	.25	.08	.27
Yorkshire	.06	.23	.06	.24
West Midlands	.06	.24	.06	.25
East Midlands	.04	.19	.05	.22
East Anglia	.03	.15	.02	.14
South West	.06	.23	.07	.25
Wales	.02	.15	.02	.14
Scotland	.07	.25	.06	.24
Region missing	.35	.47	.32	.46
Married	.62	.48	.73	.44
Children present	.65	.47	.97	.15
Child under 4 years	.28	.45	.29	.45
English score	19.64	11.68	20.82	10.67
English missing	.19	.39	.14	.35
Part-Time	.35	.47	.72	.44
Private	.56	.49	.60	.48
Union	.39	.48	.27	.44
>50 emps at work	.10	.31	.05	.22
Works with VDU	.53	.49	.36	.48
Primary production	.03	.18	.04	.21
Manufacturing	.02	.14	.02	.15
Construction	.09	.29	.16	.37
Retailing	.05	.23	.05	.22
Transport	.09	.28	.10	.30
Property	.12	.32	.15	.36
Industry Missing	.55	.49	.42	.49
Managerial	.03	.18	.01	.08
Technical	.36	.48	.25	.43
Skilled non-manual	.28	.45	.34	.47
Skilled manual	.10	.30	.06	.24
Partly skilled	.15	.36	.23	.42
Unskilled	.04	.21	.08	.28

Note Sample 1 N=4574 Sample 2 N=1265

Table 5.16 Comparison of Returns to Experience using Potential and Actual Experience Measures

Variable	*I*	*II*
Degree	.492*	.632*
	(.029)	(.027)
Tech	.381*	.379*
	(.025)	(.024)
Alevel	.228*	.260*
	(.056)	(.046)
Olevel	.219*	.206*
	(.028)	(.027)
Low	.115*	.085*
	(.032)	(.030)
Potential experience	.234*	
	(.059)	
Potential exp^2	-.010*	
	(.002)	
Actual experience		.054*
		(.011)
Actual exp^2		-.0008
		(.0005)
Constant	.321	.820*
	(.409)	(.066)
Controls	None	None
Adj R^2	.159	.173
F	143.6	173.3
N	4574	4574

Note 1. Dependent variable: Log hourly wage. 2. Sample: All females in work in 1991. 3. White adjusted standard errors in parentheses for heteroscedasticity. 4. Asterisk notes significance at 5% level.

Table 5.17 Returns to Experience and Functional Form

Variable	*I*	*II*	*III*
Degree	.632*	.294*	.303*
	(.027)	(.026)	(.026)
Tech	.379*	.188*	.196*
	(.024)	(.023)	(.023)
Alevel	.260*	.058	.055
	(.046)	(.043)	(.044)
Olevel	.206*	.070*	.069*
	(.027)	(.024)	(.024)
Low	.085*	.042	.042
	(.030)	(.025)	(.025)
Actual experience	.054*	.027*	.027*
	(.011)	(.010)	(.010)
Actual exp^2	-.0008	-.0008	-.0009*
	(.0005)	(.0004)	(.0004)
Job Tenure			.007*
			(.002)
North		-.219*	-.228*
		(.038)	(.038)
North West		-.172*	-.175*
		(.029)	(.029)
Yorkshire		-.156*	-.165*
		(.032)	(.032)
West Midlands		-.160*	-.168*
		(.029)	(.029
East Midlands		-.164*	-.166*
		(.036)	(.036)
East Anglia		-.161*	-.164*
		(.044)	(.044)
South West		-.140*	-.144*
		(.033)	(.033)
Wales		-.268*	-.274*
		(.032)	(.032)
Scotland		-.226*	-.229*
		(.031)	(.031)
Region missing		-.124*	-.126*
		(.020)	(.020)
Married		.092*	.087*
		(.015)	(.015)
Kids		-.165*	-.160*
		(.019)	(.019)
Young kid		.124*	.120*
		(.018)	(.018)
English: Test Bottom 20%		-.070*	-.068*
		(.020)	(.020)
21-40th pctile		-.053*	-.050*

		(.021)	(.021)
41-60th pctile		-.064*	-.061*
		(.030)	(.030)
61-80 pctile		-.043*	-.040
		(.022)	(.022)
English missing		.008	.010
		(.021)	(.021)
Part-time now		-.287*	-.277*
		(.017)	(.017)
Private		-.056*	-.053*
		(.016)	(.016)
Union		.089*	.074*
		(.015)	(.015)
Large firm		.137*	.121*
		(.025)	(.025)
Uses VDU		.206*	.200*
		(.016)	(.016)
Primary		.108*	.111*
		(.044)	(.044)
Manufacturing		.014	.020
		(.052)	(.052)
Construction		.012	.013
		(.040)	(.040)
Retailing		.177*	.170*
		(.045)	(.045)
Transport		.169*	.172*
		(.044)	(.0440
Property		.143*	.148*
		(.038)	(.038)
Ind miss		.193*	.193*
		(.037)	(.037)
Constant	.820*	1.349*	1.336*
	(.066)	(.069)	(.069)
Controls	No	Yes	Yes
Adj R^+	.173	.381	.396
F	173.3*	111.0*	113.6*
N	4574	4574	4574

Note 1. Dependent variable: Log hourly wage. 2. Sample: All females in work in 1991. 3. White adjusted standard errors in parentheses for heteroscedasticity. 4. Asterisk notes significance at 5% level.

Table 5.18 Alternative Functional Forms of Actual Experience

Variable	*I*	*II*	*III*	*IV*
Degree	.297*	.294*	.283*	.298*
	(.027)	(.025)	(.026)	(.026)
Tech	.193*	.193*	.194*	.189*
	(.024)	(.023)	(.023)	(.023)
Alevel	.049	.049	.038	.049
	(.076)	(.044)	(.045)	(.043)
Olevel	.067*	.067*	.069*	.065*
	(.026)	(.024)	(.024)	(.024)
Low	.044	.045	.048	.040
	(.031)	(.025)	(.025)	(.025)
Actual experience	.020*			
	(.007)			
Actual exp^2 / 100	.072			
	(.081)			
Actual exp^3 / 1000	-.076*			
	(.034)			
Exp. Spline <12		.018*		
		(.004)		
Exp. Spline 12-16		-.029*		
		(.009)		
Exp. Spline 16 +		.0008		
		(.025)		
Actual Exp. < 6			-.055*	
			(.037)	
Actual Exp. 6 - 7			-.092*	
			(.047)	
Actual Exp. 7 - 8			-.073*	
			(.042)	
Actual Exp. 8 - 9			-.036*	
			(.032)	
Actual Exp. 9 –10			.067	
			(.032)	
Actual Exp. 10-11			.072	
			(.027)	
Actual Exp. 11-12			.112*	
			(.030)	
Actual Exp. 12-13			-.022	
			(.029)	
Actual Exp. 13-14			-.009	
			(.026)	
Actual Exp. 14-15			.041	
			(.024)	
Actual Exp. 15-16			.072*	
			(.029)	
Full-Time				.020*
				(.006)

Full-Time^2				-.0007*
				(.0003)
Part-Time				-.003
				(.006)
Part-Time^2				.0004
				(.0004)
Current job tenure	.008*	.008*	.008*	.007*
	(.002)	(.002)	(.002)	(.002)
Part Time now	-.279*	-.279*	-.278*	-.258*
	(.017)	(.017)	(.018)	(.019)
Private	-.052*	-.052*	-.053*	-.054*
	(.016)	(.016)	(.016)	(.016)
Union	.072*	.072*	.072*	.073*
	(.016)	(.015)	(.015)	(.015)
Large Firm	.120*	.121*	.120*	.121*
	(.022)	(.024)	(.025)	(.025)
Uses VDU	.198*	.198*	.197*	.198*
	(.015)	(.016)	(.016)	(.016)
Constant	1.317*	1.334*	1.474*	1.394*
	(.070)	(.059)	(.050)	(.056)
Adj R^2	.379	.379	.390	.379
F	72.6*	72.6*	90.29*	104.5*
N	4574	4574	4574	4574

Note 1. Dependent Variable: Log real hourly wage. 2. Sample: All females in work in 1991.
3. White adjusted standard errors in parentheses for heteroscedasticity. 4. Asterisk notes significance at 5% level. 5. Regional, industry, marital status, reading and child dummies, as in Table 5.17, are also included but these results are not reported.

Table 5.19 Alternative Specifications of Experience and Time Out

Variable	*I*	*II*	*III*	*IV*	*V*	*VI*	*VII*	*VIII*
Degree	.286*	.312*	308*	.304*	.276*	.323*	.313*	.308*
	(.027)	(.026)	(.026)	(.027)	(.032)	(.031)	(.031)	(.031)
Tech	.195*	.195*	.195*	.195*	.169*	.166*	.166*	.166*
	(.024)	(.024)	(.024)	(.024)	(.029)	(.029)	(.029)	(.029)
Alevel	.062	.061	.049	.050	.063	.070	.050	.051
	(.076)	(.076)	(.076)	(.077)	(.081)	(.081)	(.081)	(.080)
Olevel	.075*	.071*	.071*	.072*	.044	.040	.039	.041
	(.026)	(.026)	(.026)	(.026)	(.031)	(.031)	(.031)	(.031)
Low	.046	.042	.043	.044	.040	.037	.035	.036
	(.031)	(.030)	(.030)	(.030)	(.038)	(.038)	(.037)	(.038)
Pre out	.012*		-.0001	-.0007	.015*		-.0002	-.0012
	(.002)		(.002)	(.002)	(.004)		(.003)	(.003)
Pre out^2	-.0008*				-.0004*			
	(.0002)				(.0002)			
Post out	.038*		.003*	.003*	.059*		.015*	.015*
	(.007)		(.001)	(.001)	(.008)		(.003)	(.003)
Post out^2	-.002*				-.003*			
	(.0006)				(.0006)			
Pre * post	-.003*				-.003*			
	(.0005)				(.0006)			
Last Outspell (h_1)				-.021*				-.016*
				(.003)				(.004)
Previous Outspell(h_0))				-.010*				-.003
				(.004)				(.004)
Outspell		-.016*	-.017*			-.015*	-.011*	
		(.005)	(.003)			(.007)	(.003)	
Out^2 / 100		.0001				-.0001		
		(.0005)				(.0006)		
Current job	.005*	.005*	.005*	.006*	-.001	.006*	-.002	-.001
tenure	(.002)	(.002)	(.002)	(.002)	(.003)	(.002)	(.003)	(.003)
Constant	1.346*	1.547*	1.540*	1.544*	1.223*	1.540*	1.469*	1.464*
	(.062)	(.054)	(.061)	(.061)	(.075)	(.066)	(.081)	(.076)
Adj. R^2	.383	.382	.383	.384	.429	.417	.423	.425
F	70.2*	75.4*	73.6*	72.1*	52.8*	54.1*	54.1*	53.1*
N	4570	4570	4570	4570	2823	2823	2823	2823

Notes: 1: Dependent Variable: Log real hourly wage. 2. Sample: Specifications I, II, III and IV, All female workers Specifications V, VI, VII and VIII, All female workers with some out spell.
3.White adjusted standard errors in parentheses. 4. Asterisk notes significance at 5% level.
5. Regional, industry, marital status, reading and child dummies, as in Table 5.17, are also included but results not reported.

Table 5.20 Effect of Full-Time/Part-Time Work on Returns to Experience and Time Out

Variable	*I*	*II*	*III*	*IV*
Degree	.303*	.296*	.302*	.300*
	(.027)	(.027)	(.029)	(.032)
Tech	.199*	.191*	.165*	.165*
	(.024)	(.025)	(.025)	(.029)
Alevel	.065	.056	.083	.080
	(.044)	(.076)	(.053)	(.081)
Olevel	.074*	.068*	.045	.044
	(.024)	(.026)	(.027)	(.031)
Low	.040	.038	.037	.041
	(.025)	(.031)	(.030)	(.038)
Actual experience	.015		.028	
	(.010)		(.015)	
Actual exp^2	-.0009*		-.002	
	(.0003)		(.0007)	
Full-Time		.011		.005*
		(.007)		(.0009)
Full-Time^2		-.001		-.001*
		(.001)		(.0004)
Part-Time		-.013*		-.032*
		(.006)		(.008)
Part-Time^2		-.0004*		.002*
		(.0005)		(.0006)
Outspell	-.024*	-.023*	-.038*	-.032*
	(.006)	(.006)	(.010)	(.008)
Out^2 / 100	-.0005	-.0004	-.001	-.0005
	(.0005)	(.001)	(.001)	(.001)
Part-time Work	-.267*	-.248*	-.236*	-.226*
	(.017)	(.019)	(.020)	(.022)
Current job tenure	.006*	.007*	.007*	.007*
	(.002)	(.002)	(.002)	(.002)
Constant	1.522*	1.569*	1.555*	1.716*
	(.074)	(.070)	(.101)	(.091)
Adj. R^2	.384	.34	.433	.429
F	72.2*	68.8*	73.6*	49.8*
N	4570	4570	2823	2823

Note 1. Dependent Variable: Log real hourly wage. 2. Sample: Specifications I, II, All female workers. Specifications III, IV, female workers with some out spell. 3. White adjusted standard errors in parentheses for heteroskedasticity. 4. Asterisk notes significance at 5% level.
5. Regional, industry, marital status, reading and child dummies, as in Table 5.17, are also included but not reported. 6. F test of equality between full-time and part-time experience variables = 6.44 (F(2,4527)) in II and 6.35 (F(2,2780)) not accepted.

Table 5.21 Estimates of Time Out Effect by Type of Non-work Spell

Variable	*I*	*II*	*III*	*IV*
Degree	.241*	.198*	.234*	.180*
	(.026)	(.031)	(.026)	(.030)
Tech	.189*	.142*	.190*	.144*
	(.022)	(.025)	(.023)	(.025)
Alevel	.079	.079	.083	.096
	(.043)	(.049)	(.044)	(.053)
Olevel	.076*	.040*	.076*	.045*
	(.023)	(.026)	(.024)	(.026)
Low	.043	.045	.040	.044
	(.025)	(.031)	(.025)	(.029)
Actual exp			.019	.030
			(.010)	(.015)
Actual exp^2			-.0009	-.0019
			(.0004)	(.0007)
Unemp	-.079*	-.082*	-.084*	-.097*
	(.011)	(.013)	(.012)	(.014)
Unemp^2	.0043*	.004*	.0046*	.004*
	(.0011)	(.001)	(.0011)	(.001)
Educ	.060*	.072*	.055*	.055*
	(.009)	(.011)	(.010)	(.012)
Educ^2	-.0037*	-.004*	-.0034*	-.004*
	(.0008)	(.001)	(.0008)	(.001)
Home	-.046*	-.062*	-.052*	-.078*
	(.0061)	(.007)	(.0065)	(.009)
Home^2	.0021*	.003*	.0026*	.003*
	(.0005)	(.0005)	(.0006)	(.0006)
Other	-.042*	-.034*	-.045*	-.048*
	(.018)	(.018)	(.018)	(.019)
Other^2	.0006	-.0004	.0009	-.0003
	(.0019)	(.002)	(.0020)	(.002)
Current job	.004*-	.002	.005*-	.003
tenure	(.001)	(.002)	(.002)	(.002)
Constant	1.554*	1.570*	1.482*	1.570*
	(.047)	(.058)	(.075)	(.058)
Adj. R^2	.406	.462	.408	.469
F	102.3*	76.45*	97.3*	72.47*
N	4570	2823	4570	2823

Notes. 1 Dependent Variable: Log real hourly wage. 2. Sample: Specifications I and III, All female workers. Specifications II and IV, All female workers with some out spell. 3. White adjusted standard errors in parentheses. 4. Asterisk notes significance at 5% level. 5. Regional, industry, marital status, reading and child dummies, as in Table 5.17, were also included but results are not reported. 6. F test of equality between unemployed and home-time spell variables = 5.27 (F(2,4525)) in I and 5.56 (F(2,4523)) in III not accepted. F test of equality between unemployed and home-time spell variables = 2.09 (F(2,2778)) in II and 1.92 (F(2,2776)) in IV not rejected.

Table 5.22 Test of Robustness of Estimates to Leverage and Outliers in Residuals

Variable	I	II	III	IV	V	VI
Degree	.303*	.311*	.296*	.298*	.234*	.251*
	(.027)	(.020)	(.027)	(.020)	(.027)	(.020)
Tech	.199*	.193*	.191*	.179*	.190*	.189*
	(.024)	(.018)	(.024)	(.018)	(.024)	(.017)
Alevel	.065	.041	.056	.029	.083	.061
	(.076)	(.057)	(.076)	(.057)	(.075)	(.034)
Olevel	.074*	.062*	.068*	.049*	.077*	.071*
	(.026)	(.019)	(.026)	(.019)	(.026)	(.018)
Low	.040	.046*	.038	.029	.040	.044
	(.031)	(.023)	(.031)	(.023)	(.030)	(.020)
Actual exp	.015*	.016*			.019*	.023*
	(.007)	(.006)			(.007)	(.005)
Actual exp^2	-.0009*	-.0009*			-.0009*	-.0011*
	(.0003)	(.0003)			(.0003)	(.0002)
Out spell	-.024*	-.022*	-.023*	-.020*		
	(.006)	(.005)	(.006)	(.005)		
Out spell^2	.0005	.0004	.0004	.0001		
	(.0005)	(.0004)	(.0005)	(.0004)		
Unemp					-.084*	-.092*
					(.015)	(.010)
Unemp^2					.0046*	.0061*
					(.0017)	(.0010)
Educ					.055*	.056*
					(.009)	(.008)
Educ^2					-.0034*	-.0034*
					(.0010)	(.0010)
Home					-.052*	-.051*
					(.007)	(.005)
Home^2					.0026*	.0028*
					(.0007)	(.0005)
Other					-.045*	-.042*
					(.020)	(.020)
Other^2					.0009	.0007
					(.0024)	(.0034)
Job Tenure	.006*	.007*	.007*	.007*	.004*	.005*
	(.001)	(.001)	(.002)	(.001)	(.002)	(.001)
Part time sp			-.013*	-.023*		
			(.006)	(.005)		
Part time sp^2			.0004	.001*		
			(.0005)	(.0003)		
Full-time sp			.011	.008		
			(.007)	(.005)		
Full-time sp^2			-.0008*	-.0006*		
			(.0003)	(.0003)		
Part-time now	-.267*	-.242*	-.248*	-.215*	-.239*	-.217*
	(.017)	(.013)	(.019)	(.014)	(.018)	(.013)

Private	-.053*	-.055*	-.053*	-.054*	-.044*	-.044*
	(.016)	(.012)	(.016)	(.012)	(.016)	(.012)
Union	.073*	.088*	.071*	.081*	.071*	.085*
	(.015)	(.012)	(.016)	(.011)	(.015)	(.011)
Large firm	.119*	.101*	.120*	.099*	.124*	.106*
	(.022)	(.017)	(.022)	(.017)	(.022)	(.016)
Uses VDU	.197*	.193*	.194*	.191*	.177*	.169*
	(.015)	(.011)	(.015)	(.011)	(.015)	(.012)
Constant	1.522*	1.493*	1.569*	1.580*	1.482*	1.458*
	(.074)	(.058)	(.070)	(.052)	(.074)	(.050)
Adj R^2	.384	.527	.384	.530	.402	.551
F	72.17*	123.78*	68.80*	119.54*	67.62*	151.4*
N	4570	4410	4570	4416	4570	4409

Note 1. Sample: I, III, V: All women in work in 1991; Sample: II, IV, VI: All women in work in 1991 with observations with excessive leverage and outliers omitted. 2. White adjusted standard errors in parentheses. 3. Asterisk notes significance at 5% level. 4. Regional, industry, marital status, reading and child dummies, as in Table 5.17, are also included but not reported.

Table 5.23 Experience and Time Out Effects by Educational Attainment

Variable	Low Quals All women.	High Quals. All women	Low Quals. Some break	High Quals. Some break
Actual exp	.022	.006	.046*	-.002
	(.012)	(.016)	(.020)	(.021)
Actual exp^2	-.0007*	-.0011	-.0020*	-.0014
	(.0005)	(.0006)	(.0010)	(.0009)
Out spell	-.024*	-.024*	-.032*	-.040*
	(.008)	(.011)	(.014)	(.015)
Out spell^2	.0012	.0002	.0016	.0006
	(.0006)	(.0010)	(.0009)	(.0012)
Job Tenure	.006*	.007*	.008*	.007
	(.002)	(.002)	(.003)	(.004)
Part-time now	-.286*	-.212*	-.238*	-.206*
	(.020)	(.031)	(.023)	(.035)
Private	-.035*	-.034	-.088*	-.035
	(.019)	(.028)	(.024)	(.034)
Union	.036*	.096*	.072*	.081*
	(.019)	(.025)	(.022)	(.031)
Large firm	.181*	.057	.151*	.089*
	(.041)	(.030)	(.046)	(.040)
Uses VDU	.206*	.189*	.228*	.166*
	(.021)	(.024)	(.026)	(.031)
Constant	1.400*	1.945*	1.316*	2.105*
	(.085)	(.137)	(.121)	(.169)
Adj R^2	.375	.249	0.386	0.269
F_1	57.7*	22.4*	35.1*	17.6*
F_2		9.7*		8.2*
N	2810	1760	1665	1158

Note 1. Sample: Specifications I,II: All women in work in 1991. Specifications III,IV: Women in work in 1991 having had some break in continuous employment. 2. White adjusted standard errors in parentheses for heteroscedasticity. 3. Asterisk notes significance at 5% level. 4. Regional, industry, marital status, reading and child dummies, as in Table 5.17, are also included but results not reported.
5. F_1 is F test for joint significance of regressors. 6. F_2 is Chow test for sample split high and low education.

Table 5.23 Experience and Time Out Effects by Educational Attainment (*cont.*)

Variable	Low Quals. All	High Quals. All	Low Quals. Some out	High Quals. Some out
Out spell	-.022*	-.023*	-.018	-.041*
	(.008)	(.011)	(.012)	(.015)
Out spell^2	.0010	.0002	.0005	.0006
	(.0006)	(.0010)	(.0007)	(.0013)
Job Tenure	.006*	.007*	.006*	.006
	(.002)	(.003)	(.003)	(.004)
Part time exp	.007	-.040*	-.014	-.053*
	(.009)	(.011)	(.009)	(.014)
Part time exp^2	-.0004	.002*	.0013*	.002*
	(.0005)	(.0008)	(.0094)	(.0010)
Full-time exp	.015*	-.001	.013	-.009
	(.007)	(.014)	(.008)	(.017)
Full-time exp^2	-.0003	-.0011	-.0006	-.0013
	(.0004)	(.0006)	(.0005)	(.0009)
Part-time now	-.261*	-.198*	-.224*	-.196*
	(.022)	(.035)	(.024)	(.040)
Private	-.037	-.033	-.094*	-.036*
	(.019)	(.028)	(.024)	(.035)
Union	.036	.091*	.067*	.077*
	(.019)	(.025)	(.022)	(.031)
Large firm	.183*	.058	.155*	.091*
	(.041)	(.030)	(.045)	(.040)
VDU	.202*	.185*	.229*	.163
	(.021)	(.024)	(.027)	(.031)
Constant	1.432*	2.019*	1.484*	2.206*
	(.074)	(.123)	(.107)	(.144)
Adj R^2	0.376	0.249	0.378	0.269
F_1	55.5*	21.2*	33.5*	17.2*
F_2		9.2*		7.5*
N	2810	1760	1665	1158

Table 5.23 Effects of High and Low Educational Qualifications *(cont.)*

Variable	Low Quals. All	High Quals. All	Low Quals. Some out	High Quals. Some out
Actual exp	.024	.001	.049*	-.018
	(.012)	(.016)	(.020)	(.019)
Actual exp^2	-.0007	-.0010	-.0020*	-.0007
	(.0005)	(.0006)	(.0009)	(.0008)
Job Tenure	.005*	.004	.004	.001
	(.002)	(.002)	(.003)	(.004)
Unemp. Spell	-.049*	-.133*	-.044*	-.154*
	(.013)	(.043)	(.017)	(.047)
Unemp. Spell^2	.002*	.0028	.0015	.0058
	(.001)	(.0114)	(.0013)	(.0119)
Educ.Spell	.081*	.029*	.105*	.015
	(.032)	(.011)	(.033)	(.015)
Educ. Spell^2	-.0030	-.0020*	-.0057	-.0013
	(.0061)	(.0008)	(.0062)	(.0010)
Home Spell	-.030*	-.086*	-.046*	-.108*
	(.007)	(.018)	(.012)	(.022)
Home^2	.0018*	.0034	.0028*	.0040
	(.0007)	(.0022)	(.0008)	(.0023)
Otherout Spell	.024	-.007	-.020	-.019
	(.019)	(.060)	(.019)	(.063)
Otherout^2	-.0000	.0127	-.0005	-.013
	(.0019)	(.0112)	(.0018)	(.0112)
Part-time now	-.275*	-.163*	-.215*	-.146*
	(.019)	(.031)	(.022)	(.035)
Private	-.027	-.020	-.076*	-.018*
	(.018)	(.027)	(.024)	(.034)
Union	.035	.101*	.071*	.085*
	(.019)	(.025)	(.021)	(.030)
Large firm	.180*	.061*	.154*	.091*
	(.041)	(.029)	(.044)	(.038)
Uses VDU	.194*	.154*	.207*	.109*
	(.021)	(.024)	(.026)	(.030)
Constant	1.378*	1.987*	1.264*	2.234*
	(.086)	(.139)	(.124)	(.166)
Adj R^2	0.381	0.280	0.403	0.314
F_1	52.3*	25.2*	33.5*	21.2*
F_2		6.7*		4.6*
N	2810	1760	1665	1158

Table 5.24 Experience and Time Out Effects by Manual/Non-Manual Status

Variable	Manual	Non-Man.	Manual Some out	Non-Man. Some out
Actual exp	.021*	.008	.027*	.032
	(.006)	(.017)	(.009)	(.025)
Actual exp^2	-.0004	-.0009	-.0012*	-.0022*
	(.0003)	(.0007)	(.0004)	(.0011)
Out spell	-.021*	-.023*	-.021	-.037*
	(.007)	(.009)	(.014)	(.013)
Out spell^2	.0011*	.0001	.0009	.0007
	(.0005)	(.0008)	(.0008)	(.0010)
Job Tenure	.003	.009*	.004	.009*
	(.003)	(.002)	(.004)	(.003)
Part-time now	-.280*	-.250*	-.213*	-.246*
	(.028)	(.021)	(.033)	(.025)
Private	-.055*	-.045*	-.102*	-.062*
	(.022)	(.021)	(.028)	(.027)
Union	.142*	.033	.149*	.054*
	(.026)	(.019)	(.032)	(.023)
Large firm	.078	.119*	.057	.131*
	(.051)	(.027)	(.053)	(.034)
Uses VDU	.278*	.110*	.301*	.102*
	(.029)	(.020)	(.036)	(.024)
Constant	1.339*	1.660*	1.287*	1.656*
	(.081)	(.119)	(.121)	(.158)
Adj R^2	.431	.315	0.416	0.365
F_1	44.1*	54.8*	23.8*	40.4*
F_2		6.9*		5.7
N	1457	3113	917	1906

Note 1. Sample: Specifications I,II: All women in work in 1991. Specifications III,IV: Women in work in 1991 having had some break in continuous employment. 2. White adjusted standard errors in parentheses for heteroscedasticity. 3. Asterisk notes significance at 5% level. 4. Regional, industry, marital status, reading and child dummies, as in Table 5.17, are also included but results not reported.
5. F_1 is F test for joint significance of regressors. 6. F_2 is Chow test for sample split manual and non-manual.

Table 5.24 Experience and Time Out Effects by Manual/Non-Manual Status (*cont.*)

Variable	Manual	Non-Man.	Manual Some out	Non-Man. Some out
Out spell	-.016	-.023*	-.006	-.031*
	(.009)	(.009)	(.014)	(.011)
Out spell^2	.0007	-.0002	-.0002	.0001
	(.0007)	(.0008)	(.0008)	(.0008)
Job Tenure	.002	.010*	. 002	.008*
	(.003)	(.002)	(.004)	(.003)
Part time exp	.003	-.021*	-.017	-.039*
	(.011)	(.008)	(.013)	(.010)
Part time exp^2	.0003	.0004	.0017*	.002*
	(.0007)	(.0006)	(.0008)	(.0007)
Full-time exp	.006	.007	-.004	.010
	(.009)	(.009)	(.010)	(.012)
Full-time exp^2	.0004	-.0010*	.0005	-.0015*
	(.0005)	(.0005)	(.0006)	(.0006)
Unemp	-.254*	-.230*	-.203*	-.226*
	(.034)	(.024)	(.037)	(.027)
Unemp^2	-.059*	-.045*	-.111*	-.062*
	(.022)	(.021)	(.028)	(.027)
Educ	.144	.032	.143*	.050*
	(.026)	(.020)	(.033)	(.023)
Educ^2	.082	.118*	.067*	.132*
	(.050)	(.026)	(.053)	(.033)
Home	.280*	.106*	.306*	.097*
	(.029)	(.020)	(.035)	(.024)
Home^2	1.396*	1.700*	1.413*	1.814*
	(.079)	(.096)	(.121)	(.117)
Other				
Adj R^2	0.431	0.316	0.415	0.362
F_1	40.8*	52.7*	22.3*	39.5*
F_2		6.4*		5.4*
N	1457	3113	917	1906

Table 5.24 Experience and Time Out Effects by Manual/Non-Manual Status (*cont.*)

Variable	Manual	Non-Man.	Manual Some out	Non-Man. Some out
Actual exp	.023*	.012	.031*	.035
	(.006)	(.017)	(.009)	(.025)
Actual exp^2	-.0004	-.0010	-.0012*	-.0022*
	(.0003)	(.0007)	(.0004)	(.0011)
Job Tenure	.002	.007*	.002	.003
	(.003)	(.002)	(.004)	(.003)
Unemp	-.048*	-.101*	-.029	-.113*
	(.016)	(.017)	(.020)	(.019)
Unemp^2	.0031*	.0053*	.0011	.0057*
	(.0014)	(.0017)	(.0016)	(.002)
Educ	.094*	.043*	.108*	.045*
	(.028)	(.012)	(.029)	(.015)
Educ^2	-.0046*	-.0037*	-.0054*	-.0039*
	(.0015)	(.0014)	(.0016)	(.0015)
Home	-.028*	-.062*	-.038*	-.091*
	(.008)	(.0093)	(.014)	(.012)
Home^2	.0017*	.0030*	.0022*	.0047*
	(.0007)	(.0009)	(.0009)	(.0010)
Other	-.0095	-.077*	-.004	-.082*
	(.021)	(.030)	(.022)	(.031)
Other^2	-.0012	.0038	-.0020	-.0034
	(.0020)	(.0036)	(.0020)	(.0036)
Part-time now	-.272*	-.216*	-.191*	-.198*
	(.027)	(.021)	(.033)	(.024)
Private	-.048*	-.038	-.091*	-.051*
	(.021)	(.021)	(.028)	(.027)
Union	.133	.032	.135*	.052*
	(.026)	(.018)	(.031)	(.022)
Large firm	.093	.124*	.075*	.139*
	(.050)	(.027)	(.049)	(.032)
Uses VDU	.251*	.099*	.253*	.077*
	(.029)	(.020)	(.037)	(.024)
Constant	1.295*	1.637*	1.212*	1.664*
	(.081)	(.123)	(.126)	(.162)
Adj R^2	0.439	0.339	0.439	0.329
F_1	42.6*	52.6*	27.6*	42.1*
F_2		5.0*		4.1*
N	1457	3113	917	1906

Table 5.25 Quantile Regression Estimates of Returns To Experience and Time Out

Variable	*25th Percentile*	*Median*	*75th Percentile*	*25 th Percentile Some out*	*Median Some out*	*75th Percentile Some out*
Degree	.215*	.328*	.363*	.193*	.331*	.330*
	(.023)	(.028)	(.028)	(.030)	(.037)	(.035)
Tech	.126*	.193*	.244*	.088*	.154*	.196*
	(.021)	(.020)	(.028)	(.029)	(.028)	(.030)
A level	.122*	.046	.014	.125*	.076	.022
	(.033)	(.064)	(.077)	(.054)	(.061)	(.091)
O level	.037*	.064*	.079*	-.022	.021	.037
	(.023)	(.019)	(.026)	(.032)	(.029)	(.031)
Low	.035	.014	.023	.028	.017	.020
	(.022)	(.024)	(.025)	(.031)	(.027)	(.031)
Actual exp	.002	.005	.022*	.016	.010	.022
	(.008)	(.008)	(.011)	(.011)	(.014)	(.018)
Actual exp^2	-.0002	-.0005	-.0011*	-.0012*	-.0011	-.0016*
	(.0004)	(.0004)	(.0004)	(.0005)	(.0006)	(.0008)
Out spell	-.008	-.025	-.027*	-.029*	-.037*	-.037*
	(.007)	(.007)	(.005)	(.009)	(.009)	(.010)
Out $spell^2$	-.0006	.0008	.0011*	.0005	.0011	.0015*
	(.0006)	(.0007)	(.0004)	(.0007)	(.0008)	(.0006)
Job Tenure	.006*	.007*	.006*	.005*	.007*	.008*
	(.002)	(.002)	(.002)	(.003)	(.003)	(.003)
Part-time now	-.222*	-.252*	-.263*	-.172*	-.226*	-.266*
	(.019)	(.018)	(.020)	(.019)	(.023)	(.024)
Private	-.084*	-.061*	-.030	-.011*	-.100*	-.072*
	(.013)	(.016)	(.017)	(.017)	(.027)	(.025)
Union	.117*	.095*	.073*	.134*	.096*	.079*
	(.013)	(.016)	(.018)	(.016)	(.020)	(.023)
Large firm	.113*	.110*	.112*	.139*	.146*	.138*
	(.025)	(.023)	(.028)	(.037)	(.031)	(.034)
Uses VDU	.213*	.189*	.183*	.227*	.188*	.189*
	(.014)	(.017)	(.019)	(.019)	(.020)	(.024)
Constant	1.332*	1.579*	1.625*	1.412*	1.660*	1.752*
	(.077)	(.070)	(.084)	(.088)	(.092)	(.129)
Pseudo R^2	.305	.306	.277	.303	.332	.325
N	4570	4570	4570	2823	2823	2823

Note 1. Sample: Specifications I,II,III: All women in work in 1991. Specifications IV,V,VI: Women in work in 1991 having had some break in continuous employment. 2. Asterisk notes significance at 5% level. 3. Regional, industry, marital status, reading and child dummies, as in Table 5.17, are also included but results not reported.

Table 5.25 Quantile Regressions *(cont.)*

Variable	*25th Percentile*	*Median*	*75th Percentile*	*25 th Percentile Some out*	*Median Some out*	*75th Percentile Some out*
Degree	.233*	.313*	.350*	.199*	.318*	.334*
	(.022)	(.023)	(.032)	(.026)	(.033)	(.037)
Tech	.137*	.182*	.232*	.088*	.152*	.185*
	(.023)	(.023)	(.024)	(.029)	(.028)	(.029)
A level	.139*	.020	.010	.153*	.081	.001
	(.036)	(.059)	(.080)	(.041)	(.068)	(.083)
O level	.048*	.060*	.068*	-.008	.029	.024
	(.021)	(.022)	(.028)	(.031)	(.028)	(.029)
Low	.041	.005	.017	.035	.030	-.029
	(.023)	(.022)	(.029)	(.031)	(.026)	(.029)
Out spell	-.006	-.025*	-.028*	-.025*	-.036*	-.033*
	(.005)	(.007)	(.006)	(.008)	(.008)	(.011)
Out spell^2	.0008	.0008	.0011*	.0002	.0009	.0012*
	(.0005)	(.0007)	(.0005)	(.0007)	(.0007)	(.0006)
Job Tenure	.006*	.008*	.007*	.005	.007*	.009*
	(.002)	(.002)	(.002)	(.003)	(.002)	(.003)
Part time exp	-.017*	-.019*	-.009	-.031*	-.036*	-.018
	(.005)	(.008)	(.008)	(.008)	(.009)	(.010)
Part time exp^2	.0010*	.0009	.0002	.0020*	.0020*	.0005
	(.0004)	(.0005)	(.0005)	(.0005)	(.0006)	(.0007)
Full-time exp.	.006	.012	.010	.014	.011	.001
	(.006)	(.007)	(.006)	(.009)	(.008)	(.010)
Full-time exp^2	-.0003*	-.0009*	-.0008*	-.0013*	-.0014*	-.0007
	(.0004)	(.0004)	(.0003)	(.0005)	(.0004)	(.0005)
Part-time now	-.205*	-.228*	-.248*	-.159*	-.217*	-.254*
	(.017)	(.022)	(.021)	(.018)	(.023)	(.024)
Private	-.084*	-.057*	-.031	-.108*	-.084*	-.060*
	(.012)	(.018)	(.018)	(.016)	(.021)	(.021)
Union	.116*	.093*	.066*	.127*	.094*	.076*
	(.014)	(.018)	(.019)	(.019)	(.018)	(.022)
Large firm	.114*	.113*	.110*	.136*	.157*	.152*
	(.024)	(.023)	(.026)	(.033)	(.027)	(.030)
VDU	.208*	.187*	.175*	.231*	.191*	.179*
	(.013)	(.016)	(.019)	(.017)	(.021)	(.022)
Constant	1.322*	1.579*	1.746*	1.471*	1.732*	1.873*
	(.058)	(.070)	(.079)	(.075)	(.068)	(.122)
Pseudo R^2	.307	.307	.277	.306	.333	.324
N	4570	4570	4570	2823	2823	2823

Table 5.25 Quantile Regressions *(cont.)*

Variable	*25th Percentile*	*Median*	*75th Percentile*	*25 th Percentile Some out*	*Median Some out*	*75th Percentile Some out*
Degree	.197*	.232*	.287*	.151*	.181*	.226*
	(.049)	(.026)	(.031)	(.032)	(.035)	(.040)
Tech	.140*	.170*	.220*	.102*	.127*	.188*
	(.049)	(.021)	(.030)	(.028)	(.028)	(.036)
A level	.175*	.025	.021	.193*	.067	.010
	(.058)	(.050)	(.064)	(.042)	(.046)	(.088)
O level	.049*	.058*	.057	.002	.031	.031
	(.072)	(.023)	(.031)	(.029)	(.027)	(.034)
Low	.038	.007	-.004	.057	.018	-.022
	(.066)	(.028)	(.034)	(.028)	(.029)	(.036)
Actual exp	.006	.015*	.018	.022*	.014	.022
	(.008)	(.007)	(.013)	(.008)	(.012)	(.020)
Actual exp^2	-.0002	-.0007*	-.0009	-.0012*	-.0011*	-.0017
	(.0003)	(.0003)	(.0005)	(.0004)	(.0005)	(.0009)
Job Tenure	.005*	.005*	.003*	.004	.003	.003
	(.002)	(.002)	(.002)	(.003)	(.002)	(.002)
Unemployment spell	-.058*	-.086*	-.085*	-.081*	-.091*	-.088*
	(.029)	(.011)	(.023)	(.016)	(.014)	(.025)
Unemp^2	.0033	.0046*	.0047*	.0045*	.0041*	.0041*
	(.0018)	(.0015)	(.0030)	(.0014)	(.0016)	(.0027)
Education spell	.072*	.061*	.039*	.065*	.061*	.042*
	(.021)	(.011)	(.011)	(.017)	(.016)	(.013)
Educ^2	-.0058*	-.0028	-.0022*	-.0053*	-.0027*	-.0023
	(.0029)	(.0018)	(.0009)	(.0021)	(.0014)	(.0013)
Home spell	-.022*	-.048*	-.061*	-.048*	-.069*	-.083*
	(.007)	(.007)	(.009)	(.009)	(.009)	(.011)
Home^2	.0006	.0028*	.0033*	.0019*	.0035*	.0040*
	(.0007)	(.0006)	(.0008	(.0008)	(.0007)	(.0008)
Other spell	-.013	-.050*	-.021	-.028	-.056*	-.052
	(.044)	(.018)	(.032)	(.021)	(.021)	(.024)
Other^2	-.0019	.0018	.0014	.0011	.0021	.0010
	(.0053)	(.002)	(.0046)	(.0041)	(.0030)	(.0026)
Part-time now	-.223*	-.229*	-.240*	-.154*	-.191*	-.207*
	(.053)	(.019)	(.021)	(.021)	(.021)	(.025)
Private	-.076*	-.055*	-.042*	-.097*	-.072*	-.070*
	(.015)	(.016)	(.024)	(.017)	(.019)	(.023)
Union	.109*	.081*	.071*	.129*	.092*	.072*
	(.030)	(.013)	(.021)	(.020)	(.019)	(.022)
Large firm	.110*	.133*	.089*	.146*	.154*	.144*
	(.026)	(.021)	(.023)	(.040)	(.030)	(.032)
Uses VDU	.190*	.174*	.156*	.188*	.179*	.128*
	(.019)	(.016)	(.025)	(.022)	(.020)	(.021)
Constant	1.294*	1.505*	1.689*	1.314*	1.593*	1.812*
	(.080)	(.061)	(.112)	(.085)	(.099)	(.151)
Pseudo R^2	.316	.323	.292	.326	.363	.354
N	4570	4570	4570	2823	2823	2823

Table 5.26 Heckman Selectivity Adjusted for Participation Wage Equations

Variable	*Probit in work*	*Wage Eqn*	*Wage Eqn*	*Wage Eqn*
	I	**II**	**III**	**IV**
Degree	.548*	.302*	.315*	.252*
	(.058)	(.030)	(.029)	(.030)
Tech	.056*	.196*	.207*	.208*
	(.049)	(.027)	(.027)	(.028)
A level	1.049*	.056	.065	-.113
	(.237)	(.079)	(.079)	(.078)
O level	-.472*	.068*	.081*	-.093
	(.054)	(.028)	(.028)	(.028)
Low	.319*	.041	.050	-.056
	(.064)	(.031)	(.031)	(.031)
Kids		-.158*	-.153*	-.105*
		(.020)	(.020)	(.020)
Young kid		.121*	.106*	.061*
		(.019)	(.019)	(.019)
Number of kids	-.403*			
	(.016)			
Age of youngest	.029*			
	(.005)			
Partner out of wk	.031			
	(.032)			
Part time 2nd last job	.467*			
	(.043)			
Married	.125*	.088*	.086*	.085*
	(.036)	(.015)	(.015)	(.015)
Actual Experience		.025*		.021*
		(.007)		(.007)
Actual Exp2		-.0009*		-.0010*
		(.0002)		(.0003)
Unemployment spell				-.085*
				(.015)
$Unemp^2$				.005*
				(.002)
Education spell				.055*
				(.009)
$Educ^2$				-.003*
				(.001)
Home spell				-.052*
				(.007)
$Home^2$				.003*
				(.001)
Other spell				-.045*
				(.020)
$Other^2$				-.001
				(.002)
Current job tenure		.007*	.003	.004*
		(.002)	(.002)	(.002)
Pre out experience			-.004*	
			(.002)	
Post out experience			.005	
			(.002)	
Outspell			-.019*	
			(.003)	
λ		-.003	.032	.057
		(.042)	(.041)	(.041)
Constant	.220*	1.348*	1.563*	1.426*
	(.060)	(.077)	(.065)	(.081)

Log L	-4152.62			
χ^2	1005.74			
R^2	.108	.378	.383	.402
F		72.2	71.9	66.2
N	7162	4574	4570	4570

Note 1. Dependent variables: (I) Work Dummy, (II, III and IV) Log real hourly Wage. 2. Standard errors in parentheses. 3. Asterisk notes significance at 5% level. 4 Regional, industry, marital status, reading and child dummies, as in Table 5.17, were also included but these results are not reported.
5. Sample: All female workers

Table 5.27 Selectivity Adjusted Treatment Model Wage Equations

Variable	*Probit: Time out*	Wage Estimates		
		II (Unadjusted)	**III (Treatment)**	**IV (Instrumented)**
Degree	.340*	.313*	369*	.306*
	(.059)	(.027)	(.028)	(.027)
Tech	-.051	.202*	.185*	.202*
	(.052)	(.024)	(.024)	(.024)
A level	.5129*	.081	.176*	.063
	(.243)	(.076)	(.078)	(.077)
O level	-.047	.076*	.064*	.073*
	(.057)	(.026)	(.026)	(.026)
Low	-.142*	.041	.015	.040
	(.068)	(.030)	(.031)	(.031)
Kids		-.129*	-.039	-.160*
		(.023)	(.026)	(.019)
Young Kid		.126*	.116*	.127*
		(.017)	(.017)	(.017)
Number of kids	.290*			
	(.018)			
Age of youngest	.014*			
	(.005)			
Partner out of work	-.044			
	(.033)			
Part time 2nd last job	.289*			
	(.048)			
Married	-.064*	.089*	.089*	.085*
	(.036)	(.015)	(.015)	(.015)
Time out		-.066*	-.058*	-.042
		(.015)	(.015)	(.039)
Current job tenure		.006*	.005*	.008*
		(.002)	(.002)	(.001)
Part time now		-.274*	-.246*	-.282*
		(.017)	(.017)	(.017)
Private		-.052*	-.054*	-.052*
		(.016)	(.016)	(.016)
Union		.075*	.075*	.074*
		(.022)	(.016)	(.016)
Large firm		.123*	.124*	.119*
		(.022)	(.022)	(.056)
VDU		.203*	.196*	.201*
		(.015)	(.015)	(.015)
λ			.422*	
			(.067)	
Constant	.153*	1.537*	1.246*	1.536*
	(.063)	(.055)	(.071)	(.065)
log L	-3858.12			
χ^2	618.9*			
Adj R^2	.074	.379	.384	.376
F		76.3*	76.0*	75.5*
N	4567	4567	4567	4567

Note 1. Dependent variables: (I) Break Dummy, (II, III and IV) Log real hourly Wage. 2. Standard errors in parentheses. 3. Asterisk notes significance at 5% level. 4 Regional, industry, marital status, reading and child dummies, as in Table 5.17, were also included but these results are not reported.
5. Sample: All female workers in work in 1991.

Table 5.28.a. Multinomial Logit Estimates of Labour Force Status

Variable	*Continuous worker* ***I***	*Time out Current job tenure < 2 years* ***II***	*Time out Current job tenure >= 2 years* ***III***
Years of educ	-.0012	-.002	.006*
	(.0013)	(.002)	(.002)
North	-.155	-.142*	-.118
	(.095)	(.105)	(.097)
South east	-.147	-.138	-.149
	(.089)	(.099)	(.092)
Midlands	-.008	.124	.085
	(.095)	(.102)	(.096)
Celts	-.007	-.068	-.069
	(.122)	(.136)	(.122)
Degree	.950*	1.175*	1.321*
	(.123)	(.132)	(.120)
Tech	1.289*	1.003*	1.063*
	(.103)	(.117)	(.108)
A / O level	.962*	1.879*	.881*
	(.112)	(.125)	(.116)
Low	.726*	.442*	.406*
	(.131)	(.152)	(.143)
Married	-.052	.228*	.072*
	(.069)	(.078)	(.071)
Young kid	-1.214*	-1.061*	-1.351
	(.070)	(.077)	(.073)
Constant	-.377	-1.450*	-2.029*
	(.362)	(.380)	(.341)
log L	-9207.9		
X^2 (55)	880.9		
Pseudo R^2	.046		
N	7126		

Note 1. Base reference category: not in work. 2. Standard errors in parentheses.
3. Asterisk notes significance at 5% level. 4. Regional, industry, marital status, reading and child dummies, as in Table 5.17, were also included but these results not reported.
5. Dependent variable: Labour force status. 6. Sample: All women.

Table 5.28.b. Multinomial Logit Estimates of Labour Force Status

Dependent Variable: Labour force status Sample:All women

Variable	*Continuous Worker* ***I***	*Home out T < 2 yrs* ***II***	*Other out T < 2 yrs* ***III***	*Home out T >= 2 yrs* ***IV***	*Other out T >= 2 yrs* ***V***
Years of ed	-.001	-.006	-.008*	-.006	-.011*
	(.002)	(.002)	(.002)	(.003)	(.002)
North	-.157*	-.068*	-.248*	-.037*	-.236*
	(.095)	(.128)	(.145)	(.102)	(.116)
South-East	-.047	-.082	-.213	-.040	-.210
	(.089)	(.125)	(.134)	(.132)	(.107)
Midlands	.004	.338	-.193	-.141	-.041
	(.095)	(.121)	(.146)	(.134)	(.111)
Celts	.007	-.019	-.138	-.016	-.098
	(.112)	(.168)	(.185)	(.174)	(.140)
Degree	.953*	.687*	1.686*	.505*	1.846*
	(.123)	(.167)	(.184)	(.171)	(.151)
Tech	1.290*	.851*	1.234*	.712*	1.422*
	(.103)	(.141)	(.173)	(.140)	(.142)
A / O level	.959*	.956*	.692*	.692*	1.101
	(.112)	(.146)	(.198)	(.148)	(.154)
Low	.726*	.477*	.309	.303	.500
	(.131)	(.177)	(.246)	(.180)	(.195)
Married	-.058	.603*	.203	.504*	-.217*
	(.069)	(.101)	(.104)	(.102)	(.082)
Young kid	-1.212*	-.831*	-1.368	-1.677*	-1.156
	(.070)	(.091)	(.113)	(.111)	(.085)
Constant	-.395	-.727	-3.385*	-.317	-3.676*
	(.362)	(.525)	(.472)	(.567)	(.377)
Log L	-10927.6				
X^2 (55)	1294.6				
Pseudo R^2	.056				
N	7126				

Note 1. Base category: not in work 2. Standard errors in parentheses. 3.Asterisk notes significance at 5% level. 4. Regional, industry, marital status, reading and child dummies, as in Table 5.17, were also included but these results are not reported.

Table 5.29 Groot and van Ours Specification

	I	*II*	*III*	*IV*
Pre out Work Experience	-.001 (.002)	-.001 (.002)	-.003 (.002)	-.003 (.002)
Duration of last out spell	-.020* (.003)	-.016* (.003)		
Home*Last out spell			-.021* (.004)	-.015* (.004)
Ed*Last out spell			.005 (.011)	.006 (.010)
Unemp*Last out spell			-.046* (.011)	-.043* (.011)
Other *Last out spell			-.063* (.014)	-.058* (.014)
Rebound	.007 (.008)	.043* (.017)		
Reb * home			-.020 (.012)	.019 (.021)
Reb * education			.063* (.018)	.093* (.027)
Reb * unemployed			-.010 (.012)	.025 (.023)
Reb * other			.066* (.018)	.098* (.027)
Current job tenure -2 yr	.006* (.002)	.003 (.002)	.005* (.002)	.002 (.002)
Λ_1 Continuous Work		.891* (.249)		.333* (.140)
Λ_2 All out back less than 2 years		-.579 (.303)		
Λ_3 All out back >=2 years		.631* (.254)		
Λ_4 Home out back less than 2 years				-.385 (.234)
Λ_5 Home out back >=2 years				-.063 (.256)
Λ_4 All other out back less than 2 yrs				.070 (.260)
Λ_5 All other out back >=2 yrs				-.073 (.174)
Constant	1.537* (.058)	1.311* (.090)	1.556* (.057)	1.471* (.072)
Adj. R^2	.382	.386	.389	.397
F	72.1*	69.3*	65.7*	61.1*
N	4574	4574	4574	4574

Note 1. Standard errors in parentheses. 2. Asterisk notes significance at 5% level.
3.Regional, industry, marital status, education, reading and child dummies, as in Table 5.17, also included but results not reported. 4. Dependent Variable: Log real hourly wage. 5. Sample: All women in work in 1991. 6. F test for equality of coefficients for last spell unemployed or in home care = 4.84 (F(1, 4528) in III and 5.86 F(1, 4523) in IV not accepted. 7 . F test for equality of rebound effects following unemployment or home time = 0.40 (F(1, 4528) in III and 0.04 (F(1, 4523) in IV not rejected.

Table 5.30 Mean Changes in Wages and Experience 1981 to 1991

	1981	*1991*	*Difference*
Total			
Hourly Wage	1.5	1.8	+0.3
	(0.7)	(0.6)	(0.8)
Work experience	3.9	13.7	+9.8
	(2.4)	(3.1)	(3.0)
Non-work experience	0.1	1.7	+1.7
	(0.8)	(2.5)	(2.5)
Unemployment	0.1	0.2	+0.1
	(0.4)	(0.8)	(0.5)
Childcare	0.1	0.9	+0.8
	(0.6)	(2.1)	(1.6)
Manual			
Wage	1.4	1.5	+0.1
	(0.7)	(0.5)	(0.8)
Work experience	4.4	13.7	+9.3
	(2.3)	(3.4)	(3.4)
Non-work experience	0.2	2.0	+1.8
	(0.7)	(2.9)	(2.8)
Unemployment	0.1	0.3	+0.2
	(0.3)	(1.1)	(0.8)
Childcare	0.2	1.4	+1.2
	(0.8)	(2.7)	(2.0)
Non-Manual			
Wage	1.6	1.9	+0.3
	(0.8)	(0.5)	(0.8)
Work experience	3.7	13.7	+10.0
	(2.4)	(2.9)	(2.8)
Non-work experience	0.1	1.6	+1.6
	(0.8)	(2.4)	(2.4)
Unemployment	0.1	0.2	+0.1
	(0.4)	(0.6)	(0.4)
Childcare	0.1	0.7	+0.6
	(0.5)	(1.8)	(1.4)

Note. 1. Sample sizes 2960 of which 834 manual and 2126 non-manual. 2. Standard deviations in parentheses.

Table 5.31 Fixed Effect Estimation: Controlling for Unobserved Heterogeneity

Variable	*Levels 1991*	*Difference*	*Levels 1991*	*Difference*	*Levels 1991*	*Difference*
	I	**II**	**III**	**IV**	**V**	**VI**
Experience	.063*	.081*			.035	.036*
	(.018)	(.010)			(.019)	(.009)
Exp^2	-.002*	-.0012*			-.0015*	-.0007
	(.0007)	(.0004)			(.0008)	(.0004)
Out spell			-.029*	-.022		
			(.011)	(.014)		
Out^2			-.001	.005*		
			(.001)	(.001)		
Full time			.010	.014		
			(.012)	(.014)		
Full time ^{2}			-.001	-.001		
			(.001)	(.001)		
Part time			-.072*	-.033*		
			(.009)	(.011)		
Part time ^{2}			.004*	.001		
			(.001)	(.001)		
Home out					-.116*	-.051*
					(.013)	(.020)
Home out ^{2}					.0062*	-.001
					(.0013)	(.003)
Unemployed					-.136*	-.120*
					(.018)	(.050)
Unemployed ^{2}					.0087*	-.004
					(.0023)	(.006)
Educ					.084*	.121
					(.014)	(.088)
$Educ^2$					-.0057*	.004
					(.0014)	(.007)
Other					-.043	.024
					(.027)	(.090)
Other ^{2}					-.0005	-.015
					(.0025)	(.010)
Any kids	-.193*	-.084*	-.094*	-.094*	-.064*	-.088*
	(.024)	(.035)	(.026)	(.035)	(.026)	(.035)
Kid more than 2 kids	-.155*	-.162*	-.106*	-.192*	-.086*	-.153*
	(.024)	(.038)	(.023)	(.039)	(.023)	(.038)
Married	.101*	.083*	.088*	.085*	.072*	.082*
	(.020)	(.033)	(.020)	(.033)	(.020)	(.033)
Constant	1.218*	.237	1.784*	.383*	1.563*	.114
	(.112)	(.066)	(.086)	(.034)	(.126)	(.071)
Adjusted R^2	.091	.048	.143	.029	.274	.050
F	46.7*	29.1*	51.5*	10.5*	50.8*	13.9*
N	2955	2955	2955	2955	2955	2955

Note. 1. In the ordinary least squares model, the dependent variable is the log of the real hourly wage. In the first difference model, the dependent variable is the change in the log of the hourly wage:

$$\Delta \ln \text{wage} = (\ln \text{wage}_{i\,t+1} - \ln \text{wage}_{i\,t})$$

The first difference values represent the change in variables between Sweep 4 and Sweep 5 (1981 to 1991). 2. White adjusted standard errors in parentheses. 3. Asterisk notes significance at 5% level. 4. All wages are in 1991 pounds. 5. F tests on equality of full and part-time coefficients =18.54 (F(2, 2933) in III and 4.49 (F(2, 2950) in IV not accepted. 6. F tests on equality of unemployed and home time coefficients = 0.56 (F(2, 2929) in V and 1.35 (F(2, 2946) in VI not rejected.

Chapter 6

British Evidence on the Effects of Re-Entry on the Gender Wage Gap

6.1 Introduction

Chapter 2 confirmed the well-known observation that women earn less than men, but that this gender pay gap has been falling in recent years. It is also apparent from Chapters 2 and 5 that women who work part-time have lower hourly earnings than women who work full-time and that this full-time - part-time gap has been rising at the same time as the gender wage gap has narrowed (see also Paci and Joshi (1996) and Harkness (1996)). There is an enormous literature (see amongst others Blau and Kahn (1992)) aimed at estimating the size of the gender pay gap and the proportions of the gap that can be ascribed to various explanations (which generally means differences in characteristics and coefficients between men and women in earnings functions). However, what passes as an explanation for economists often seems less than satisfactory to non-economists. For example, consider the following possible explanations for the gender pay gap:

"Women are less likely to be promoted than men so their wage growth is lower and so they tend to get stuck in the lower-paying jobs."

"From the time they enter the labour market, women are in the low-paying jobs."

"The interruption to labour market careers of women caused predominantly by care responsibilities leads to lower earnings for women."

Of course, economists are fully aware of these competing possible explanations for the gender pay gap, but it is simply very hard, if not impossible, to assess the relative importance of them with many of the data sets and the approaches that are commonly used. For example, with simple cross-sections of earnings and characteristics (which are the most commonly used), little more can be done than to regress earnings on characteristics and then to decompose the pay gap into a part which is the result of

differences in characteristics and a part which is the result of differences in coefficients. Speculation can then be carried out on the causes of the results found (see, for example, Brown, Moon and Zoloth (1980) who look at differences in occupation, Gronau (1988) who looks at differences in skill intensity, and Swaffield (1997) who looks at differences in motivation). Of course, the results from these studies can be interpreted as shedding light on the explanations proposed above. For example, finding significantly different effects of children on the earnings of men and women is plausibly interpreted as the consequences of interrupted labour market careers. Mincer and Polachek (1974), Corcoran and Duncan (1979), Mincer and Ofek (1982), Cox (1984), and Chapter 5 have established the connection between interruptions and reduced earnings for women.

Given the cross section data available, it is unclear what more can be done. However, once there is the opportunity to use panel data, other possibilities are extended. There is a large literature on whether better measures of labour market experience can help in explaining the gender pay gap (for example, Groot and van Ours (1994), Albrecht, Edin, Sundstrom and Vroman (1996)). Panel data containing information on labour market histories makes such estimation possible. Chapter 5 suggests that estimates of the returns to experience can be biased if potential, rather than actual, experience measures are used. Chapter 5 also shows that women who have a career break receive lower earnings than women who do not and that it takes time to make up these lost earnings.

Some researchers have attempted to model the evolution of earnings over the whole life cycle (for studies of the evolution of male earnings see Abowd and Card (1989), Gottschalk and Moffitt (1995), for the US and Dickens (1996) for the UK). The aims of this Chapter are more modest (in part because we have access to a very short panel). We show how, with a minimum of just two observations on earnings and employment, a different decomposition of the gender pay gap can be derived which can shed further light on the sources of the disadvantage of women in the labour market.

The decomposition can be described straightforwardly. We divide the workers observed in a single cross-section into two groups: those with continuous employment and those who have had some period of non-employment in the past year (whom we shall call entrants following the terminology of Gregg and Wadsworth (1996)[1]). The latter are the same types of women who we observed as having had time out in Chapter 5 (although the data set used here is different). Continuous workers may have had several employers over their working lives but have never left employment. The current average wage can be thought of as being a weighted average of the average wages of these two groups with the weight being determined by the proportion of labour market entrants. For those who have been continuously employed the current wage can be written as the previous wage plus their wage growth. Having written the average wage this way, we can decompose the pay gap between men and women into differences in these components. This is what this Chapter does. It should be emphasised that this decomposition is not the only one that might be done, but we think that its usefulness should be judged by the insights into the explanation of the gender pay gap it produces. For example, if it was found that the gender pay gap could be ascribed largely to the fact that there were differences in wage growth, this might suggest that discrimination in promotion or job change decisions was important.[2] On the other hand, if it were found that differences in entrant shares were the most important factor in explaining the wage gap it would suggest the need to examine differences in labour market transitions.

This Chapter uses a British longitudinal data set, the British Household Panel Survey, (BHPS) to investigate the impact of re-entry on explaining the gender wage gap. Section 6.2 outlines the decomposition in more detail. Section 6.3 gives an outline of the data and sample construction, whilst section 6.4 presents the empirical evidence. Section 6.5 concludes.

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[1] This terminology might be found a bit confusing as the term entrants is sometimes reserved for those workers entering the labour market for the first time from full-time education. Our entrants include these workers but also those who are re-entering paid employment after a period of non-work.

[2] For more evidence on pay and promotion see Booth, Francesconi and Frank (1998). For a summary of the evidence on job change and wage growth see Topel (1991) and Topel and Ward (1990). In what follows, we do not distinguish between these two hypotheses, concentrating instead on the continuous worker-entrant divide.

6.2 Gender Pay Decomposition

Introduction

In this Section, we introduce the decomposition of the wage gap. In the following subsection, we demonstrate the use of this decomposition when we analyse the differences in wages between the genders. In the subsequent subsection, we follow a similar procedure but we account for the differences between full and part-time work of women. The next Section provides information about the data set that we use for the study.

6.2.1 Oaxaca Decomposition

The conventional approach to the measure of pay differences between men and women stems from the Blinder (1973) and Oaxaca (1973) original method of decomposing differences in the mean pay gap into differences in characteristics and differences in the returns to these characteristics. The differences in the returns to characteristics are then traditionally ascribed to discrimination. Defining the percentage wage gap between mean male and female wages as,

$$\text{Gap} = \frac{\overline{w}_m - \overline{w}_f}{\overline{w}_f} = \frac{\overline{w}_m}{\overline{w}_f} - 1 \qquad (6.1)$$

$$\text{So that,} \quad \text{Gap} + 1 = \frac{\overline{w}_m}{\overline{w}_f} \qquad (6.2)$$

$$\text{Thus} \quad \ln(\text{Gap} + 1) = \ln(\overline{w}_m) - \ln(\overline{w}_f) \qquad (6.3)$$

Let the mean male and female log wage depend on a set of characteristics, Z, which include a set of personal, human capital and job-specific characteristics, according to the preferences of the researcher, so that we have,

$$\ln(\overline{w}_m) = \overline{Z}_m'\hat{\beta}_m \quad \text{and} \quad \ln(\overline{w}_f) = \overline{Z}_f'\hat{\beta}_f \qquad (6.4)$$

Thus, the gap may be decomposed as,

$$\ln(\text{Gap} + 1) = \overline{Z}_m'\hat{\beta}_m - \overline{Z}_f'\hat{\beta}_f \qquad (6.5\text{ (a)})$$

$$= \overline{Z}_m'\left(\hat{\beta}_f - \Delta\hat{\beta}\right) - \overline{Z}_f'\hat{\beta}_f \qquad (6.6\text{ (a)})$$

$$= \Delta\overline{Z}'\hat{\beta}_f - \overline{Z}_m'\Delta\hat{\beta} \qquad (6.7\text{ (a)})$$

The first term can be interpreted as predicting differences in earnings from a wage equation estimated for women and allowing characteristics to vary across gender. The second term captures the extent of residual 'discrimination'.

Equally,

$$\ln(\text{Gap}+1) = \bar{Z}_m'\hat{\beta}_m - \bar{Z}_f'\left(\Delta\hat{\beta}+\hat{\beta}_m\right) \qquad (6.5\text{ (b)})$$

$$= \Delta\bar{Z}'\hat{\beta}_m - \bar{Z}_f'\Delta\hat{\beta} \qquad (6.7\text{ (b)}).$$

This can be interpreted as evaluating pay gaps according to a male base wage equation. Differences in the two approaches can, and do, lead to differences in the extent of pay discrimination. The literature often reports two sets of results or takes a weighted average following the work of Oaxaca and Ransom (1994).

6.2.2 A New Decomposition

Given the availability of panel data, a richer decomposition may be derived, which can account for the possible explanations for the gender pay gap outlined in the introduction. Suppose that there were N_0 workers in employment last year with a log wage w_{oi}. For each of these workers, define an indicator variable θ_i which takes the value 1 if the worker has been in continuous employment since last year, and 0 if the worker is no longer in employment. For those workers who have been in continuous employment, let us define g_i to be the change in their log wage (so that this is approximately the rate of growth of their wage). Suppose, in the course of a year, there are E_1 labour market entrants who each have a wage w_j^e. Then the average wage observed at time 1 must be given by the weighted average of the wages of the two types of workers, (continuous and entrants)[3]:

[3] For those with θ=0 (non-workers) we obviously cannot define g but in what follows how we specify g for these people is irrelevant.

$$\overline{w_1} = \frac{\sum_{i=1}^{N_0} \theta_i (w_{0i} + g_i) + \sum_{j=1}^{E_1} w_j^e}{N_0 \sum \theta_i + E_1} \tag{6.8}$$

where the denominator gives the total employed in the population at time 1 and the first term is the average wage of job stayers at time 1.

Since $\Sigma\theta_i g_i = N_0 \overline{\theta g}$ and $\Sigma w_j^e = E_1 \overline{w^e}$, then rearrangement of (6.8) leads to:

$$\overline{w_1} = \frac{N_0 \overline{\theta g} + \sum_{i=1}^{N_0} \theta_i w_{0i} + E_1 \overline{w^e}}{N_0 \bar{\theta} + E_1} \tag{6.9}$$

where a bar over a variable denotes a mean and the mean of g is only taken over those who remain in continuous employment. In turn (6.9) can be rearranged as:

$$\overline{w_1} = \frac{N_0 \bar{\theta} . \left(\bar{g} + \overline{w_0} + \frac{Cov(w_{0i}, \theta_i)}{\bar{\theta}} \right) + E_1 \overline{w^e}}{N_0 \bar{\theta} + E_1} \tag{6.10}$$

where $Cov(w_0, \theta) = \Sigma\theta\, w_0 - N_0\, \overline{w_0}\, \overline{\theta_0}$.

This can be written as,

$$\overline{w_1} = (1 - \alpha) \left(\bar{g} + \overline{w_0} + \frac{Cov(w_{0i}, \theta_i)}{\bar{\theta}} \right) + \alpha \overline{w^e} \tag{6.11}$$

$$\text{where } \alpha \equiv \frac{E_1}{\bar{\theta} N_0 + E_1}$$

where α represents the share of entrants in current employment. Equation (6.11) says that the current average wage is a weighted average of the average wage of new entrants and the average wage of continuing workers, whose current average wage is the average

previous wage, $\overline{w_0}$, plus average wage growth, $\bar{g}$, plus a covariance term (which is essentially the correlation of job retention with the previous wage.) If this covariance term is positive (which it generally is), then high wage workers are less likely to leave employment so that the average wage among continuing workers is higher than the previous period's average wage.

If we are in a steady state, then we can further simplify the above formula. Suppose we are in a static steady state with constant wage growth and employment. Then, as employment is constant, it must be the case that inflows into employment must equal outflows and that:

$$\alpha = 1 - \bar{\theta} \tag{6.12}$$

so that the share of new entrants, the inflow rate, α, in the steady state equals the risk of leaving employment for existing workers. Then, dividing through by α in (6.11) the steady state average wage can be written as:

$$\bar{w} = \overline{w^e} + \frac{1-\alpha}{\alpha}\left(\bar{g} + \frac{Cov(w_{0i}, \theta_i)}{1-\alpha}\right) \tag{6.13}$$

In this formulation, the average wage is the average entrant wage plus the average annual growth of real wages for continuing workers multiplied by $(1-\alpha)/\alpha$ together with the covariance of employment loss with wages. Since α is the outflow rate and $1/\alpha$ is the average duration of job stayers in the employed population, then $(1-\alpha)/\alpha$ represents the expected number of periods of wage growth.[4] It should be stressed that everything we have done so far is simply manipulation of identities and the terms may themselves be influenced by other factors. It is clear that if we want to understand the difference in wages across groups (say men and women) we can think about this difference as being made up of different components of (6.13). These different components can all be given natural interpretations in terms of the three explanations of the gender pay gap discussed in the introduction. Wage growth for workers in continuous employment is connected with promotion (same firm) or job change (different firm); entrant wages are concerned with gender pay gaps from the moment of entry; and the entrant share is concerned with interruptions to labour market careers.

It should be emphasised that the split of current employees into the two groups of entrants and continuous employees are not the only ones that might be done and are themselves heterogeneous groups. We might, for example, think of breaking them down further. For example, our entrants can be thought of as consisting of two types of workers: those first entering the labour market after full-time education and those re-entering employment after a period of unemployment, sickness or domestic responsibilities. In fact, only 3 per cent of entrants in the BHPS are new entrants who have just completed full-time education, so that sample sizes prevent us from splitting our entrants in this way. Similarly, those in continuous employment could be divided into those in the same job, those who have changed job but remained with the same employer and those who have changed employer. We do include controls for whether an individual has changed jobs below, but it is sample sizes again that prevent us from doing a more thorough disaggregation along these lines.

6.2.3 The Full Time - Part Time Gap

We can apply a similar decomposition to the earnings of full-time (FT) and part-time (PT) women to try to discover the origin of the differences in their wages. However, there is an additional complication here, as individuals can move between FT and PT states. Given this, it is simple to think of those who have been in continuous employment as being divided into two groups: those who were previously employed FT and those who were previously employed PT. The average current wage will then be a suitably weighted average of the earnings of these two groups of workers and the entrants.

Let us introduce some notation. Suppose there are N_{tk} workers at date t (t=0,1) in state k (k=FT, PT) and E_{tk} entrants. Let the variable θ_{kl} take the value one if an individual was in state k in period 0, has remained in continuous employment and is in state l this period (k,l=FT,PT). Also, denote by g_{kl} the change in the log wage for those in continuous employment and in state k at date 0 and state l at date 1. On this basis, the

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[4] From the algebra, $(1-\alpha)/\alpha = (N_0\ \bar{\theta})/E_1$.

population of FT workers, $\overline{\theta_f} N_{0f} + E_f$ can be written as $\overline{\theta_{ff}} N_{0f} + \overline{\theta_{pf}} N_{0p} + E_f$, and the entrant share in the population of FT workers, α_f, is given by $\frac{E_f}{\overline{\theta_{ff}} N_{0f} + \overline{\theta_{pf}} N_{0p} + E_f}$.

Then, from (6.13), we have the following expression for the average full-time wage:

$$\begin{aligned}\overline{w_{1f}} = & \frac{\overline{\theta_{ff}} N_{0f}}{\overline{\theta_{ff}} N_{0f} + \overline{\theta_{pf}} N_{0p} + E_f}\left(\overline{w_{0f}} + \frac{Cov(w_{0f}, \theta_{ff})}{\overline{\theta_{ff}}} + \overline{g_{ff}}\right) \\ & + \frac{\overline{\theta_{pf}} N_{0p}}{\overline{\theta_{ff}} N_{0f} + \overline{\theta_{pf}} N_{0p} + E_f}\left(\overline{w_{0p}} + \frac{Cov(w_{0p,} \theta_{pf})}{\overline{\theta_{pf}}} + \overline{g_{pf}}\right) \\ & + \frac{E_f}{\overline{\theta_{ff}} N_{0f} + \overline{\theta_{pf}} N_{0p} + E_f} \overline{w_f^e} \end{aligned} \quad (6.14)$$

This has the following interpretation. The first term is the share of current full-time workers who have been in continuous employment and were previously full-time multiplied by their average wage today. The latter can be written as their current wage yesterday plus a covariance term plus their average wage growth. The term on the second line is then the share of workers who are currently FT, but who were part-time multiplied by their average current wage. The term on the final line is the share of entrants multiplied by their average wage. There is obviously an equivalent formula for PT workers:

$$\begin{aligned}\overline{w_{1p}} = & \frac{\overline{\theta_{pp}} N_{0p}}{\overline{\theta_{pp}} N_{0p} + \overline{\theta_{fp}} N_{0f} + E_p}\left(\overline{w_{0p}} + \frac{Cov(w_{0p}, \theta_{pp}}{\overline{\theta_{pp}}} + \overline{g_{pp}}\right) \\ & \frac{\overline{\theta_{fp}} N_{0f}}{\overline{\theta_{pp}} N_{0p} + \overline{\theta_{fp}} N_{0f} + E_p}\left(\overline{w_{0f}} + \frac{Cov(w_{0f,} \theta_{fp})}{\overline{\theta_{fp}}} + \overline{g_{fp}}\right) \\ & + \frac{E_p}{\overline{\theta_{pp}} N_{0p} + \overline{\theta_{fp}} N_{0f} + E_p} \overline{w_p^e} \end{aligned} \quad (6.15)$$

Now let us turn to the data to see how these decompositions work in practice.

6.3 Data

Our data is drawn from the first 5 waves of the British Household Panel Study (BHPS), covering the period from 1991-95, (for more details see Chapter 3), a period of recession in which unemployment peaked in 1993, followed by the beginning of

economic recovery. We restrict our attention to employees and use net hourly wages including overtime as our wage measure. In the "Living in Britain" Individual Questionnaire of BHPS, individuals were asked to give information on their take-home pay (after tax, National Insurance, pensions and union dues) for the last time they were paid. They were subsequently asked to say for which time period this wage was paid and whether this was their usual take-home pay. From this, we have constructed hourly wages. We remove from the sample all wages below 50 pence and all above £100 an hour, as these may be mismeasured and create outliers in our sample. The remaining hourly wages were deflated using New Earnings Survey average weekly earnings and weekly hours indices for full-time workers for the whole economy, to a base of January 1991. The average wage in our sample on this measure should then be constant over time (if we regress the adjusted wage on a time trend, the trend is not significant).[5] This facilitates pooling across waves and highlights the fact that our interest lies in wages measured relative to the average wage change for men and women. To be part of the computation of wages, an individual must have been in employment either now or previously, but the decomposition of average wages which we use also requires the availability of other information, such as details of schooling and job tenure, which further restricts our sample. The following groups of people in our sample are identified:

(a) Those employees in employment at the previous interview, but no longer in employment.
(b) Those not in employment at the previous interview, but in employment now.
(c) Those in employment at both interviews, and with no intervening period of non-employment.
(d) Those in employment at both interviews, but with some intervening period of non-employment.

In addition, those in employment in both periods require information on the intervening period (from the job history records) to be available in order to check whether they have had any intervening period of non-employment. To try to ensure that this restriction did

[5] An alternative means of indexing wages would be to deflate by the Retail Price Index. This would then mean that the average wage level would grow across the sample period.

not lead to under-representation of those in continuous employment, we limited our sample (entrants and continuous workers) to those for whom the job history information was available, even if this information was not strictly necessary for our entrants.[6]

Table 6.1 provides information on the loss in sample size from these restrictions. For example, there are 9249 observations for men who were employees at the time of last interview, of which 7696 were in employment when next interviewed. The need for job history information through the intervening period reduces the sample to 7317 observations. Of these, 7078 have been in continuous employment but not necessarily with the same employer (group (c) in our decomposition), but only 6387 have both wage and personal and job characteristics information. Amongst those currently in employment, there are 239 who were in employment when last interviewed but who had a subsequent break in employment, 182 of whom have information on wages and characteristics. These are our group (d) and we will only use information on their current average wages in the decomposition. This means throwing away wage change information for group (d), since the wage change for this group does not enter the decomposition. The total stock of entrants is (d) together with those in work now who were not in work at the previous interview date, of which there are some 452 men with wage and characteristic information, (row 18). From Table 6.1 (a), we can see that there are relatively small numbers of people in group (d) (the tenth row is the relevant one), so we cannot have a separate group for these people. In terms of their average wages (not shown) these individuals are, as we might expect, between groups (b) and (c), but they are much closer to group (b) than (c). For this reason, we choose to put them in with the labour market entrants.

6.4 Results of the Decomposition

6.4.1 Introduction

In this section, we present the results of the decomposition. The first subsection includes the results of the gender pay gap and the following subsection provides the results when we analyse the gap accounting for differences in full- and part-time work. We then go on to provide an insight into a longer run view of the gender wage gap.

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[6] Entrants could have been defined simply by using a job tenure criterion.

Finally, we conclude this section with a detailed analysis of the components of the decomposition that we have used.

6.4.2 Results of the Gender Pay Gap

Table 6.2 summarises the mean annual log hourly wage change across the sample. The mean annual wage growth is around 2.6 per cent exhibiting marginally higher wage growth for women over the period. There is large variation around the mean, median wage growth is 1.1 log points and around 46 per cent of the sample are measured with zero or negative wage growth between interview dates. There is little difference in wage growth distribution between men and women. Mean wage growth in full-time jobs is around 1.5 per cent higher than wage growth in part-time jobs. The distribution of full-time wage growth lies generally to the right of the part-time wage growth distribution, with the exception of the top decile. This is consistent with the lower returns to part-time experience observed in Chapter 5. Figure 6.1 confirms that wage growth declines with the age of worker, as to be expected, since wage levels tend to grow with age whilst promotions tend to fall with age.

Table 6.3 presents our basic decomposition of the average wage in each year. The average hourly wage for men is around £6.17 and the average hourly wage for women is around £4.44, (see the total column for the mean log wage: log values of 1.82 and 1.49 respectively). The raw wage gap is 36 log points in 1992 falling to 32 log points by 1995, (row 1). This is basically consistent with the trends observed in the gender wage gap in other data sets and confirmed by the GHS data in Chapter 2. Table 6.3 also breaks down the log wage into the different components of Equation (6.13).

It is apparent that the bulk of the gender pay gap this year is 'explained' by the gender pay gap in the previous year (row 2). However, as Equation (6.13) shows, it is the other components which are more fundamental in the sense of explaining the gender pay gap in the long-run, so it is on these components that we will focus. It should be apparent that there is quite considerable variation in these components from year to year, so that our discussion will focus on the average, paying particular attention to the variables where the differences do seem to be systematic. This year-to-year variation could be the product of the relatively small sample sizes in the BHPS or because there is

considerable cyclical variation in the factors we will study. It is a pity that we only have five waves of data with which to work as certain conclusions must inevitably be somewhat speculative although below we do look at information from other data sets to try to get some idea of longer-run trends.

Taking the five years together, wage growth for those in continuous employment seems very similar for both men and women (2.1 points for men and 2.4 for women), with growth actually being higher for women than men in 1993 and 1995 though the pattern is reversed in 1994. This might be thought somewhat surprising given that we might expect that promotions are important sources of wage growth and that women's access to higher-paid positions within firms is restricted by the so-called "glass ceiling" (see Gregg and Machin (1994)). However, we should remember that wage growth and promotions are likely to be somewhat easier to obtain at lower rungs on the job ladder. So the fact that women only have the same wage growth as men when they are concentrated on the lower rungs of the ladder could be taken as indication that, given their position, they do worse in terms of wage growth. (Booth, Francesconi and Frank (1998) complement this finding. They show that promotions are as likely for women, but wage growth in promotions is lower for women). The covariance term is always positive albeit with a large unreported standard error, (row 5), indicating (as is well known from other studies, see, for example, Burgess and Rees (1996)[7]) that high-wage, high skill workers, are much less likely to leave employment. The covariance terms also do not seem to show any large systematic differences between men and women. The implication of these results is that the wage gap does not widen through the years between men and women who remain in continuous employment and that any pay gap between these men and women must have occurred on entry into employment.

Table 6.3, (row 7), does show that there is a large systematic difference in the entry wages of men and women. The average hourly entry wage for men is around £4.14. The average hourly entry wage for women is around £3.46. Note that the gender pay gap on entry is less than the gender gap in average wages, with an average gap across the years of about 18 log points or something like half the overall gender pay gap. It would seem that the stock of women in employment contains a larger share of entrants who receive

lower wages and this could explain the gender wage gap. The fact that the gender gap in entry wages is less than the average gap is consistent with evidence from other studies. For example, Manning (1996) finds that there is no gender pay gap for those workers entering the labour market immediately after leaving full-time education and Graddy and Pistaferri (1997) find that the gender pay gap for newly-graduated MBAs is about 8 log points. It is also important to note that labour market entrants earn significantly less than the average. The traditional interpretation of this is that entrants have less human capital. Chapter 5 suggests that those with time out do, indeed, earn less than continuous workers, but that the difference is not entirely due to different endowments of human capital and that the time out process may depreciate human capital or generate uncertainty among employers which leads to lower wages.

Finally, Equation 6.13 suggests that we do need to be concerned with the difference between men and women in the proportion of entrants to employment (row 8). As we would expect, the entrant share is higher for women (about 14 per cent) than men (about 11 per cent). As labour market entrants earn less than the average this will also tend to produce a gender pay gap. However, while these differences are systematic, it might also be argued that they seem to be quite small, so that it might be asked how much of the gender pay gap can be ascribed to differences in the entrant shares.

In order to assess the relative importance of the contribution of each of these components in explaining the gender gap, we take the long-run steady-state equation (6.13) and vary each of the components one by one. That is to say, we predict the long run log hourly wage for women with the female entrant shares, wage growth, covariance and entry wages and then look to see what the predicted wage will be if we use the male values for one of these components instead.

Table 6.4 gives the details. Row 2 calculates steady state wages using the male entrant shares for both men and women. Row 3 uses the female entrant shares for both sexes. The value of $(1 - \alpha)/\alpha$ for women is 6.1, while for men it is 8.1, a difference that seems quite large. The result of these substitutions leads, for example, to a predicted male log hourly wage for 1992 of 1.87 compared to the actual wage of 1.99, (rows 1and 3) and a

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[7] Note that Burgess and Rees deal explicitly with employment at a given firm rather than at any firm.

predicted female log hourly wage of 1.79 compared to an actual wage 1.67, (rows 1 and 2). As a result, the predicted gender wage gap in 1992 falls to around 20 log points: two-thirds of the total wage gap (compare column 3 in rows 1 and 2). Rows 4 and 5 vary log entry wages and hold everything else constant. The predicted wage gap now falls to around 10 log points. Rows 6 and 7 vary the continuing job wage change and hold other factors constant. Continuous worker wage growth explains nothing of the wage gap in 1992. This pattern is generally repeated across all years. So, on this basis, it would seem that something like two-thirds of the overall gender pay gap may be ascribed to differences in pay among labour market entrants, one-third to differences in the proportion of entrants with little contribution from differences in wage growth. The gender difference in the entrant share helps explain why women are disproportionately concentrated among the low-paid. Entrants receive lower wages. More entrants means a lower average wage. The differential entrant share also explains why their earnings-experience profile is flatter (see also Manning (1996)) even though wage growth for those in continuous employment is approximately the same.

6.4.3 Results of the Full Time - Part Time Pay Gap

Table 6.5 presents the results of applying the decompositions in Equation (6.14) and (6.15) to the pay gap for full- and part-time women, where we have used 30 hours as the cut-off between part- and full-time work. The average pay gap seems quite stable over this period at around 22 log points (row 1). There are several points worth noting about the results reported in Table 6.5. First, there are very few transitions between full- and part-time status (rows 11 and 12).[8] Only something like 6 per cent of current part-time workers have been in continuous employment and were previously employed full-time with a similar proportion of full-time workers being previously part-time.[9] We note then that for many women the superior wage returns to full-time work observed in Chapter 5 are not realised through this form of transition. It is quite likely that a substantial fraction of these transitions are in fact some form of measurement error. This means that in understanding the pay gap between FT and PT women, one can treat them as approximately separate groups with little in the way of transitions between them.

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[8] Such transitions are the subject of more discussion in Chapter 7.
[9] The shortfall being made up by entrants (row 10).

Looking first at the average entrant wage (row 9), one can see that the pay gap here is very small averaging about 4 log points or only about 20 per cent of the overall gap. So, the pay gap between full- and part-time women does not emerge at the point of entry into paid work. Looking at wage growth for those in continuous employment, the picture is rather confusing. In 1992 and 1993, the average wage growth for those in continuous FT employment is not very different from those workers in continuous PT employment (compare row 4, column 1 with row 7, column 2). However, in 1994 and 1995, there is a substantial gap, with average wage growth being over 4 per cent higher for those in continuous full-time employment. This difference is then magnified by the covariance terms (rows 5 and 8) which is quite large and positive for full-time workers and close to zero for part-time workers. The implication is that, while high-wage FT workers are less likely to leave employment, the same is not true of high-wage PT workers.

The other big difference between FT and PT workers is in the entrant share (row 10). While 10 per cent of FT women are labour market entrants (a figure that is slightly lower than the overall figure for men in Table 6.3), the entrant share for PT women is closer to 20 per cent, so that one in five PT women have had a period of non-employment in the past year. From Equation (6.13), we can see that the steady-state gap depends on one minus the entrant share divided by the entrant share. This averages 9 for FT women, compared with 4 for PT women. This implies, given an average sum of the wage growth and covariance terms of 4 per cent a year, a contribution of the difference in entrant shares to the overall pay gap of 16 log points (about 75 per cent of the actual gap). So it is clear that the main source of the gap between FT and PT women is because of differences in the entrant share in the stock of these job types.

This discussion has ignored those workers who move between FT and PT status while remaining in continuous employment. While those who do move are a small group, some attention should be paid to them. What one notices when one looks at Table 6.5 is that those workers moving from FT to PT status have apparently very positive wage growth (row 7, odd columns), while those going in the opposite direction have very negative wage growth (row 4, even columns). One possible explanation for these

results is measurement error. Our hourly wage measure is computed by dividing weekly earnings by weekly hours, so it is very vulnerable to problems caused by division bias. Given that very few people seem to move between FT and PT status, a high percentage of those who are classed as having moved may be the result of mistakes in coding hours in one of the years. This can then account for the patterns of wage growth seen among those making the transitions. The alternative is that these are manifestations of the PT - FT wage gap. This would then suggest that the decomposition such as Equations 6.14 and 6.15 should be used to explain this particular pay gap. However, small cell sizes prohibited further investigation of this.

So far, we have concentrated on the pay gaps in the early 1990's. We know that there have been substantial changes in the pay gaps over time with the gender pay gap falling and the FT - PT gap rising. So we might be interested in which of the components identified above have changed.

6.5 A Longer Run View

It should be apparent from Equation (6.13) that if there were permanent changes in the main components, the observed gender pay gap would change only slowly in response to these changes. So, one way of getting some idea of likely future changes in the gender pay gap is to use Equation (6.13) to compute what the steady-state gap would be if the fundamentals remained at their current levels. If the current wage gap is above the implied long-run level then we would expect the gender pay gap to decline further while if it is above it we would expect it to rise. The implied levels of long-run wages are presented in the top row of Table 6.4 using the average values for each year, alongside the steady state gender pay gap. The numbers jump around quite a lot (largely because of the variation in wage growth, which is probably due to sampling variation of this variable), but the steady state gaps are always below the current pay gaps. Taking the average across the four years, the steady-state gender pay gap is about 4 log points less than what we currently observe. This implies that if the current gender differences in wage growth, entry wages and entrants' shares stayed the same we would expect to see a gradual narrowing of the gender pay gap with it eventually ending up at about 29 log points.

The gap between the actual and steady-state pay gap may be interpreted in another way. If the current gender pay gap is above the implied steady-state level then it must be the case that the components of the gap have been changing in such a way as to narrow the gender pay gap. So let us consider whether there is any evidence for this. This analysis must be somewhat speculative, as we cannot rely on the BHPS for data prior to 1991. There is no single data source which we can use for all the information that we require and the data that is available is not generally in an exactly equivalent form. Our information on the longer-run evolution of the entrant shares comes from the annual Labour Force Survey (LFS) conducted in the spring of every year. The LFS asks a question about current labour market status and also a question about status one year ago. This can be used to compute the fraction of workers currently in employment who were not in employment a year ago. This will obviously lead to an under-estimate of the entrant share, as we have measured it in the BHPS, as there is no information in the LFS on labour market status between the two points which we have used to classify those with interruptions to work as entrants.

Table 6.6 shows the share of entrants from 1975 to 1995 using LFS data for men and women and for FT and PT women separately.[10] The numbers from the LFS suggest that the gender gap in the entrant shares has narrowed over time, although more because the entrant shares for men are higher than 20 years ago than because female entrant shares have fallen. The entrant share for men has risen from 4 to around 7 per cent between 1975 and 1995. The entrant share for women has fallen from 12 to 11 per cent over the same period. There does seem to be good evidence that the gender gap in entrant shares is less now than it used to be. On its own, this will tend to have caused some reduction in the gender pay gap and, even if the entrants' shares stabilised at their current levels, we would expect to see some further narrowing of the gap as implied by the steady-state computations reported above.

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[10] For the years 1991-95, we can compare the LFS estimate of the entrant share with that from the BHPS on an equivalent definition to the LFS. Even on a consistent definition the entrant share in the BHPS seems to be higher than in the LFS. There may be important seasonal variation (the BHPS is conducted in the autumn, the LFS in the spring), so it is difficult to know what the exact cause of the difference is.

There are important differences between FT and PT women in the entrant shares. The entrant share for PT women, at around 15 per cent, has always been above that for FT women but the gap has widened over time largely as a result of a marked fall in the entrant share of FT women since 1985 to levels slightly below those for men. This suggests that FT jobs for women are becoming more stable. The entrant share for PT women does not show such a notable decline. This growing divergence in the entrant shares for FT and PT women is likely to be part of the cause of the widening pay gap between these two groups.

Due to the lack of wage data in the LFS before 1992, our information on the evolution of the entry pay gap comes from the General Household Survey (GHS) for 1979-91. The GHS asks a question about labour market status a year ago that is similar to the question asked in the LFS and our definition of a labour market entrant is the same as in the LFS. However, retrospective data ended in 1991. The wage information in the GHS is not ideal as it measures gross weekly earnings including overtime, but the hours measure excludes overtime, so our hourly wage has some measurement error induced by the absence of this information.[11] Table 6.7 gives the average gender pay gap for entrants and, as a comparison, the average gender pay gap in the whole sample (see also Chapter 2). The measure of the entry pay gap jumps around a bit more because the sample sizes are quite small, but it can be seen that the gender gap for entrants has always been less than the average gap and that the entrant pay gap has declined over time as has the average pay gap. In fact the trend declines in the two pay gaps are very similar. The finding from the LFS that the gap in the entrant shares has fallen means that one would expect the average gap to fall faster than the entry pay gap, so these findings, on their own, are not entirely consistent. Table 6.7 also presents the average pay gap for FT and PT women and the respective entry pay gap. We can see a marked rise in the average FT - PT pay gap from around .16 in 1979 to .25 in 1991, but no marked trend in the entrant pay gap over the period.

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[11] It should be noted that for the period 1974-79 overtime hours is available and omitting overtime hours does not seem to make that much difference, the correlation between the two measures being over 95 per cent after taking out time effects.

Now consider differences in wage growth between men and women. Our longer-run information on this comes from the New Earnings Survey (NES) conducted in April each year. As this is a panel study, we can compute wage growth for those individuals in employment in two adjacent years (so excluding entrants as defined in the GHS and LFS). Figure 6.2 plots the difference in annual wage growth for women and men for full-time adult workers.[12] We notice the very large excess in female wage growth in the early 1970's which is almost certainly the result of implementation of the Equal Pay Act. With the exception of a few isolated years, female wage growth is always above that of men and the early 1990s actually seem to be a period in which the difference is rather small. One interpretation of this result is that as women have worked their way up the job ladder, they have exploited the easy opportunities for advancement, and so it is this that accounts for the declining gaps in wage growth. It is unfortunate that these figures only relate to full-time workers, but what this suggests is that women have never been at a disadvantage in terms of wage growth if they remain in employment.

So, in terms of longer-run trends it would seem that the gender pay gap has been falling because of a declining entry pay gap and convergence in the share of entrants, but that recent changes in wage growth relative to earlier years would have tended to widen the pay gap. Comparing FT and PT women we lack the data on wage growth but it would seem that it is the growing divergence in the entrant shares which can account for the widening pay gap.

6.6 Decomposing the Decomposition

In this Section, we attempt to model the different components of the gender pay gap in trying to evaluate the extent to which the differences between men and women can be ascribed to differences in their observable characteristics or to differences in the effect of those characteristics using the familiar Oaxaca decomposition outlined above. In modelling the main components of Equation 6.13, we use a common set of regressors,

[12] Unfortunately, we do not have adequate data on PT women workers who are heavily under-sampled in the NES. See Chapter 3 for more details.

namely, experience,[13] race, marital status, number of children, education, employer size and region. We pool across all five waves to model wage growth for those in continuous employment, entry wages among labour market entrants and the probability of being an entrant among those in current employment. Descriptive statistics for these variables are summarised in Table 6.8 for men and women and in Table 6.9 for FT and PT women. Looking at Table 6.8, the overall characteristics of men and women are very similar with the only substantial differences being in average job tenure (note that a change of job in the BHPS also includes those without changes of employer), the household characteristics and the proportion working in small firms (this is consistent with the findings of Paci and Joshi (1996) and Harkness (1996) using other data sets). Once we look at the distinction between continuing workers and entrants there are more marked differences. Female entrants are much more likely to have children, and young children in particular, to work in a small enterprise, are somewhat younger than average. There is little difference in job tenure for continuing workers (we do not report job tenure for entrants, as they must have job tenure less than a year by definition).

Turning to Table 6.9, the most important differences in the characteristics of FT and PT women are in experience, education (FT women are more educated), the number of children (PT women have more, younger children) and job tenure. Perhaps surprisingly given that PT women are more likely to be entrants, they have longer job tenures than FT women. The explanation lies in the proportions of women in continuous employment that are changing jobs where FT women are much more likely to do so than PT women. This is consistent with the view that PT women may be stuck in jobs with little prospect of advancement. We start our analysis by doing the familiar decomposition of the overall wage gap.

6.6.2 The Overall Wage Gap

Table 6.10 presents the results of the estimation of standard earnings functions. The first column presents the results for all workers, the next two columns present the results of estimating separate equations for men and women, and the fourth and fifth the results

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[13] We work with potential rather than actual experience for computational simplicity. In order to compute actual experience, it would be necessary to reconcile several job history files over several waves. This enormous task is left to future work.

for FT and PT women. If we look at the coefficients for men and women, the most striking differences are to be found in the effect of children, job tenure, job changing, and in the experience profile (in the higher orders of the quartic). The number of children has no effect on male wages, but a very powerful downward effect on the wages of women (the so-called family penalty, see Waldfogel (1995) and Chapter 5). Perhaps surprisingly, the detrimental effect on female wages of very young children is smaller than the effect of older children: this is almost certainly a sample selection effect as only high-wage women can afford the high childcare costs of very young children.[14] The experience profiles for men and women are similar for something like 10 years but then decline for women earlier and faster for men leading to a gap of about 20 log points after 40 years. Women who change jobs experience a 4.7 log point wage rise, but male job changes do not appear to receive any wage gain.

Comparing FT and PT women, the most marked differences are in the experience profiles and in the effect of children. As Chapter 5 has shown, the returns to experience for part-time women are much flatter though this is partially off-set by higher returns to job tenure. The negative impact of children is seen to be exclusive to women in full-time jobs.

In what follows, we will attempt to understand how the source of these differences can be found in the individual elements of our decomposition. Table 6.14 (column 1) presents the results of a Chow test of the hypothesis of equality of coefficients between men and women and the results of the standard Oaxaca decomposition estimated from both the male and female characteristics version of the equation (6.7 (a) and (b)). As can be seen, the hypothesis of equality of coefficients is overwhelmingly rejected as we would expect, thus we are justified in running separate equations for men and women. The Oaxaca decomposition suggests that around 75 per cent of the gender pay gap can be ascribed to differences in coefficients. In contrast, differences in characteristics explain around 63 per cent of the FT - PT pay gap for women (Table 6.14, panel B, row

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[14] This raises the issue of whether we should be doing sample selection corrections to these equations. In the absence of any good instruments to identify sample selection effects we think little is added by doing this but we should retain an awareness of the possibility that some results may be driven by sample selection effects. See the previous discussion in Chapter 5.

1). However, the Chow test still does not accept the equality of the coefficients between full- and part-time women.

So far we have mirrored standard practice. Let us now extend this approach to the decomposition of the main explanatory features underlying the wage gap outlined in Equation (6.11). We do this by running OLS equations on the three principal components: namely, wage growth for those in continuous employment, entry wages and the entrant shares. We then look at what the main determinants of each these are and whether they vary across the three components in order to analyse whether an aggregate wage decomposition obscures the detailed picture.

6.6.3 Wage Growth for Those in Continuous Employment

Table 6.11 presents the results of a similar exercise to that in Table 6.10 but now the sample is restricted to workers in continuous employment and the dependent variable is the annual change in the log hourly wage. We present regressions pooled across the whole sample and regressions separately for men, women, full-time women and part-time women. What is remarkable about these regressions is that the fit is extremely poor. One of the few significant variables is the job change dummy, which suggests that changing jobs lead on average to an extra 2 per cent in wage growth. As this is the average level of wage growth in the sample this suggests that the only way in which individuals can achieve wage gains beyond the rise in average earnings is by changing jobs. Note that the premium to job changing is around 2 log points higher than the premium for job changing for women in part-time jobs. This is consistent with the implications for part-time workers found in Chapter 5.

What is notable about the wage growth equations is that the differences between the male and female equations are very small. In fact, one can accept the hypothesis of equality of coefficients (see Table 6.14). This is consistent with our earlier conclusions that gender differences in wage growth are very small. However, if anything, having children seems to raise wage growth for women more than for men, so that the child penalty for women, observed in Table 6.10, is not the consequence of lower wage growth for those in continuous employment. The Oaxaca decomposition suggests that

small differences in wage growth between men and women stems mainly from the differences in coefficients.

Turning to FT and PT women in the last two columns of Table 6.11, the coefficient differences are also not very noteworthy. There is some evidence that wage growth in part-time work at lower levels of experience is smaller but in general one can reject the hypothesis of equality of coefficients at the 5 per cent significance level. The strength of the rejection is less marked than in the case of the overall pay gap. The Oaxaca decomposition suggests that, on the basis of characteristics alone, full-time women should do better in terms of wage growth. This is largely because FT women are younger, and the estimated returns on experience suggest that wage growth becomes more negative as women age. However, overall, the coefficients are more favourable to part-time women, with the net result that part-time women have marginally higher wage changes than full-time women in the decomposition. This is perhaps another indication that groups of workers who are concentrated on the lower rungs of the job ladder have greater opportunities for wage growth.

6.6.4 Entry Wage Equations

Table 6.12 presents the results of the OLS estimates for the sample restricted to entrants and the dependent variable is the log of their hourly entry wage. Entry wages rise with experience, but less so than for the wages of all workers (see Table 6.10). Entry wages also rise with education and workplace size. Comparing the regressions for men and women, the effects of children on entry wages seem very similar so, again, this cannot be the source of the family penalty. The experience profiles are different. The female experience entry wage profiles largely mirror the experience profile for all women. The male experience entry wage profiles are much flatter than the experience profile for all men. This is reflected in Table 6.14 in the Oaxaca decompositions, where the coefficients account for more than 80 per cent of the entry wage gender gap.

Turning to the differences between entrant PT and FT women, we also find that the experience profiles are much flatter for PT women. Entry wages do not increase with age in part-time jobs to the same extent that entry wages for full-time jobs do. Women feature more heavily in part-time jobs, so this means that the entry wage gap between

men and women rises with age. However, differences in characteristics, chiefly the age-related ones, rather than coefficients explain the majority of the entry wage FT - PT gap. Once again, we can reject the hypothesis of equality of coefficients at the conventional 5 per cent significance level.

6.6.5 Entrant Equations

Table 6.13 presents the result of an 'entrant' equation. The dependent variable is now binary, taking the value one if the individual is an entrant and zero otherwise. These entrants comprise those recently hired from non-employment rather than the stock of all new hired workers. In order to facilitate the Oaxaca decomposition, we estimate a linear probability model (OLS) on a binary variable that indicates whether an individual is an entrant or not.[15] It should be remembered that the linear probability model does give consistent estimates of the average marginal effects[16] even if the standard errors are heteroscedastic (see Greene (1993)). The experience profiles confirm that entrants are dominated by younger, less qualified workers. It is here that we find big differences in the effect of children for men and women. Having young children in the household has a dramatic positive effect on the entry probability for women, but very modest and insignificant effects for men. It is in the fact that women with children are much more likely to be labour market entrants, rather than in wage growth or entry wages, that the main explanation of the pay penalty witnessed in Table 6.10 associated with having children can be found. Again, the Oaxaca decomposition suggests that it is differences in coefficients rather than characteristics that can account for the gender differences in entrant shares. It is this coefficient difference that drives much of the, albeit small, difference in entrant proportions outlined in the Oaxaca decomposition in Table 6.14.

Turning to FT and PT women, the differences in the coefficients on the regressors, with the exception of the experience profiles, are not very marked, but the Oaxaca decomposition suggests that most of the difference in entrant shares is the result of differences in coefficients, so that it is the difference in the intercept and experience that

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[15] Probit estimates were also obtained and were very similar.

[16] One of the problems with the linear probability model, namely that it may predict values outside the unit interval afflicts only 2 per cent of our sample in spite of the fact that the average value of the dependent variable is 0.1.

accounts for almost all the differences. It would seem that part-time jobs are simply more likely to be entrant jobs, whatever the other characteristics of the worker or the job.

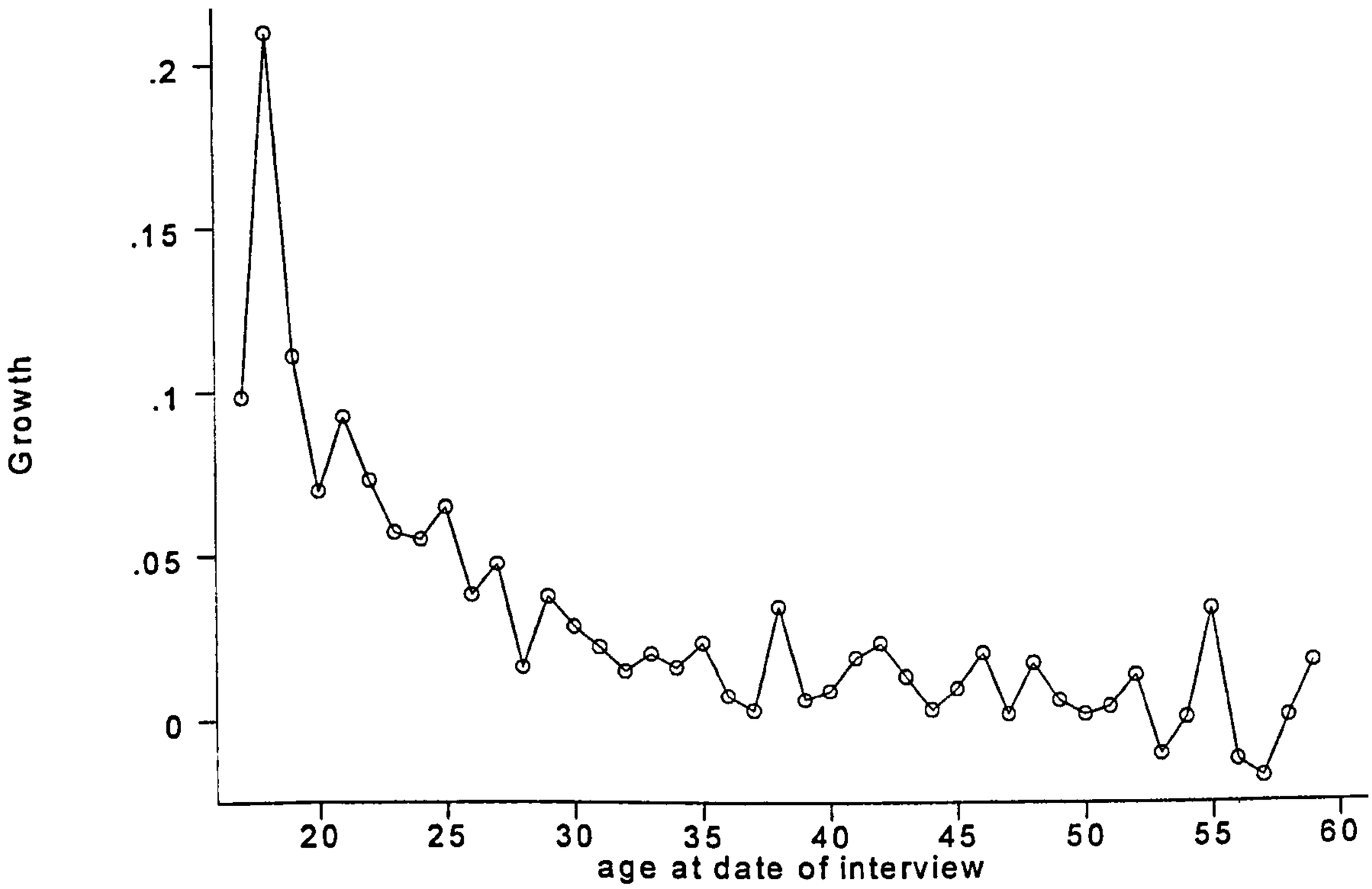
6.7 Conclusion

In this Chapter, we have presented a new decomposition of the gender pay gap, which uses limited panel information on employment transitions and wage changes. While we must always be aware that the decomposition is essentially arbitrary, we believe that it does shed some interesting light on the causes of the gender pay gap and the pay gap between FT and PT women. What this Chapter and the evidence in Chapter 5 suggests is that on entry into the labour market, after leaving full-time education, the earnings of men and women are very similar. As earnings growth while in continuous employment shows no significant gender differences, male and female earnings will follow each other closely as long as there are no breaks in paid employment. Differences in wages start to emerge once there are breaks in employment. When entering the labour market after a break, both men and women do so at lower wages, but men return at higher wages than women. This, combined with the fact that women are more likely to have breaks in paid employment, is the explanation of why women's pay increasingly falls behind the pay of men over the life-cycle. Women who work part-time are paid less than their full-time counterparts because they are much more likely to be entrants and because they have slightly lower wage growth when in paid employment.

As the bulk of the pay gap can be put down to the result of higher numbers of women having breaks in employment and the pay penalty associated with these breaks, this suggests that it is labour market interruptions that are the main cause of women's labour market disadvantage. Chapter 7 models this duration process more explicitly. As the majority of the interruptions to the labour market careers of women are caused by having children (which is largely a voluntary choice), some might be inclined to interpret our results as saying that a substantial part of the wage gap (though not necessarily a wage cut) can be ascribed to the choices of women. We would prefer to interpret this another way. Women are still often forced to choose between career and children, and given this choice, often choose children. However, such a stark choice is

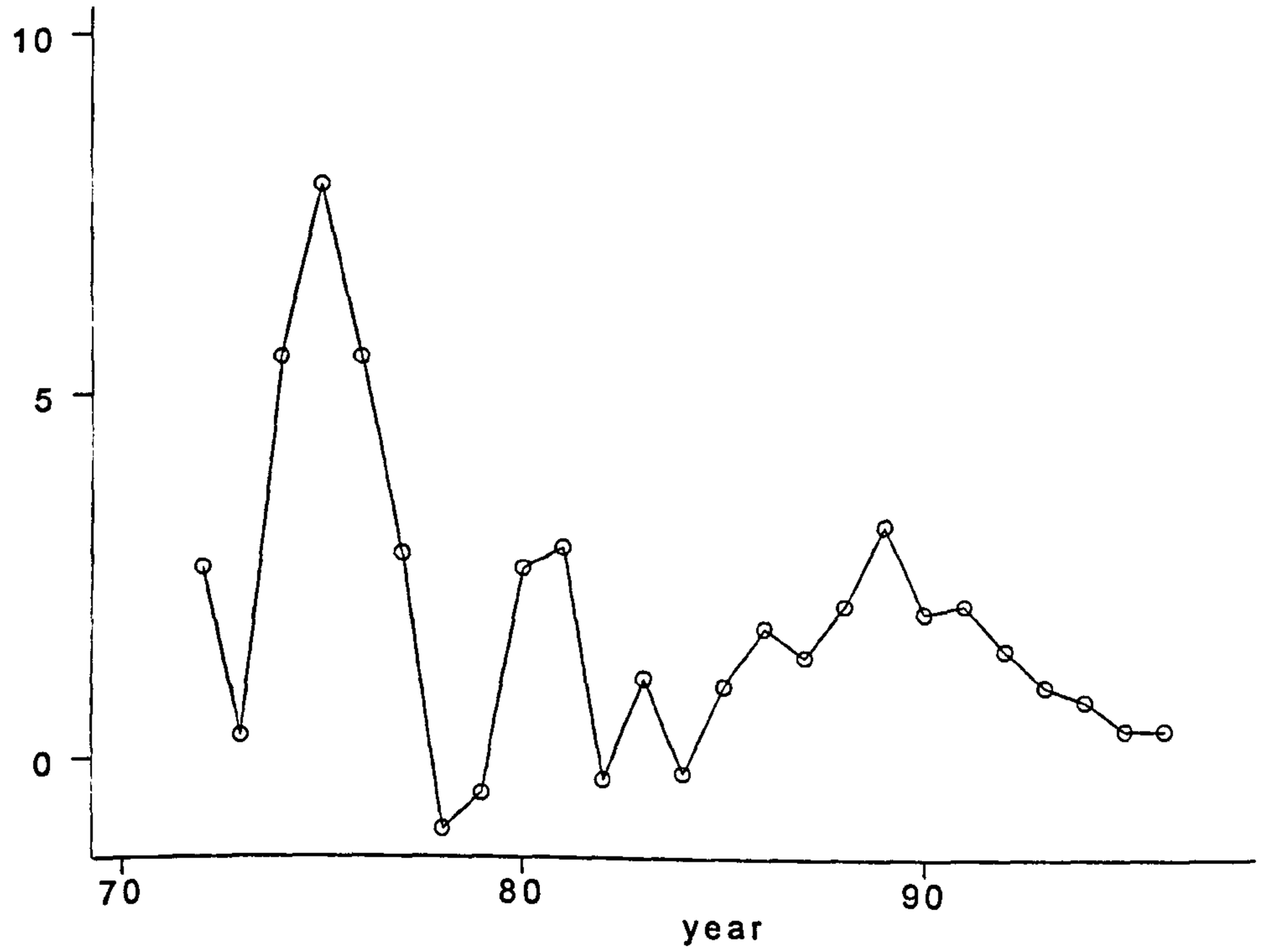
not inevitable: maternity leave entitlements can give women some opportunity to have a family and retain their pre-childbirth job. Our sample sizes here are small. Some 10 per cent of female entrants indicate that they have had a period of maternity leave, but the entry wages seem to be much higher for those who have had leave. So, maternity leave can seem to reduce both the entry pay gap and the share of entrants, which is consistent with evidence from other sources (for example, Paci and Joshi (1996)) and is also consistent with the view that it can reduce, or even eliminate, the fall in wages generally experienced when returning to the labour market after childbirth. Improving the rights and opportunities of women returning to the labour market after childbirth may be the most practical and effective way to further reduce the gender pay gap.

Figure 6.1 Annual Average Wage Change



Note. 1. Source: BHPS, various years. 2. The ordinate axis represents the percentage growth rate.

Figure 6.2 Annual Proportional Change in the Female-Male Wage Gap



Note. 1. Source: New Earnings Survey: 1972-1998.

Table 6.1.a. Sample Sizes

1991-1995	*Sample Sizes*	
	Total men	Total women
1. Previously in Employment	9249	2376
2. (1) + Currently in Employment	7696	1940
3. (2) with job history information	7317	1921
Continuous Group c		
4. (3) and continuous employment	7078	1838
5. (4) with current wage	6926	1804
6. (5) with previous wage	6744	1783
7. (6) with information on characteristics	6387	1713
Entrants Group d		
8. (3) with break in employment	239	83
9. (8) with current wage	226	83
10. (9) with information on characteristics	182	79
Employment Exits		
11. (1) + not currently in employment	793	303
12. (11) with job history information	735	301
13. (12) with previous wage	664	280
14. (1) but no record of current status	949	264
Entrants Group b		
15. not previously in employment but currently in employment	765	220
16. (15) with job history information	718	216
17. (16) with current wage	650	204
18. (17) with information on characteristics	452	165
Others		
19. currently in employment but no previous record	788	216

Table 6.1.b. Sample Sizes by Year

	1992		1993		1994		1995	
	Men	Women	Men	Women	Men	Women	Men	Women
1. Previously in Employment	2380	2376	2291	2383	2293	2346	2285	2326
2. (1) + Currently in Employment	1928	1940	1914	1939	1924	1941	1930	1915
3. (2) with job history information	1877	1921	1781	1855	1820	1886	1839	1855
4. (3) and continuous employment	1817	1838	1721	1807	1758	1826	1782	1790
5. (4) with current wage	1777	1804	1685	1773	1722	1799	1742	1764
6. (5) with previous wage	1753	1783	1645	1744	1660	1738	1686	1730
7. (6) with information on characteristics	1697	1713	1567	1662	1557	1629	1566	1616
8. (3) with break in employment	60	83	60	48	62	60	57	65
9. (8) with current wage	58	83	57	45	57	59	54	62
10. (9) with information on characteristics	50	79	48	37	43	49	41	49
11. (1) + not currently in employment	247	303	215	245	174	258	157	246
12. (11) with job history information	240	301	197	227	160	253	138	237
13. (12) with previous wage	225	280	181	220	138	224	120	218
14. (1) but no record of current status	293	264	255	194	194	185	207	185
15. not previously in employment but currently in employment	175	220	192	269	190	264	208	268
16. (15) with job history information	166	216	176	260	179	251	197	259
17. (16) with current wage	155	204	156	239	162	235	177	230
18. (17) with information on characteristics	123	165	99	186	114	180	116	175
19. currently in employment but no previous record	277	216	185	175	179	141	147	143

Table 6.2 Distribution of Annual Log Hourly Wage Change

	Total	*Men*	*Women*	*PT - PT*	*FT - FT*
Mean	.026	.023	.029	.012	.027
	(0.29)	(0.29)	(0.30)	(0.34)	(0.24)
Median	.011	.011	.012	.000	.013
10^{th} Percentile	-.218	-.227	-.208	-.258	-.188
90^{th} Percentile	.286	.288	.283	.290	.261
% <= Zero change	46.0	46.6	45.4	49.8	45.1

Note. Results pooled across 1992-1995. Standard errors in parentheses.

Table 6.3 Decomposition of the Gender Pay Gap

	1992		*Difference*	*1993*		*Difference*
	Men	Women		Men	Women	
1. Mean log wage	**1.84**	**1.48**	**0.36**	**1.83**	**1.49**	**0.34**
	(0.52)	**(0.52)**		**(0.53)**	**(0.51)**	
2. Mean log initial wage (w_0)	1.82	1.45	0.37	1.84	1.50	0.34
	(0.54)	(0.52)		(0.53)	(0.52)	
3. Mean log wage change (g)	0.029	0.029	0.00	0.008	0.015	-0.007
	(0.28)	(0.27)		(0.26)	(0.28)	
4. Covariance ÷ Proportion in Continuous Employment (Cov $w_0 \theta$ / 1-α)	0.038	0.042	-.004	0.028	0.022	0.006
5. Covariance between initial wage and current employment (Cov $w_0 \theta$)	0.034	0.036	-.002	0.025	0.019	0.006
6. Proportion in continuous employment (θ)	0.86	0.83	0.03	0.87	0.87	0.00
	(0.35)	(0.38)		(0.34)	(0.34)	
7. Mean log entrant wage (w_e)	1.45	1.25	0.20	1.41	1.23	0.18
	(0.62)	(0.51)		(0.55)	(0.52)	
8. Proportion of entrants (α)	0.11	0.14	-.03	0.11	0.14	-.03
	(0.31)	(0.34)		(0.32)	(0.35)	

Figures in parentheses are standard errors

Table 6.3 Decomposition of the Gender Pay Gap (*cont.*)

	1994		*Diffe-rence*	*1995*		*Diffe-rence*	*Total*		*Diffe-rence*
	Men	Women		Men	Women		Men	Women	
1. Mean log wage	**1.82**	**1.50**	**0.32**	**1.82**	**1.50**	**0.32**	**1.82**	**1.49**	**0.33**
	(0.55)	**(0.52)**		**(0.54)**	**(0.52)**		**(0.53)**	**(0.51)**	
2. Mean log initial wage	1.81	1.49	0.32	1.82	1.49	0.33	1.82	1.48	0.34
	(0.54)	(0.52)		(0.54)	(0.53)		(0.54)	(0.52)	
3. Mean log wage change	0.029	0.024	0.005	0.018	0.028	-0.010	0.021	0.024	-0.003
	(0.27)	(0.29)		(0.27)	(0.28)		(0.27)	(0.28)	
4. Covariance ÷ Proportion in Continuous Employment	0.030	0.030	0.000	0.033	0.023	0.010	0.033	0.029	0.004
5. Covariance between initial wage and current employment	0.027	0.026	0.001	0.029	0.020	0.009	0.029	0.025	0.004
6. Proportion in continuous employment	0.89	0.85	0.04	0.90	0.86	0.04	0.88	0.85	0.03
	(0.32)	(0.35)		(0.30)	(0.35)		(0.33)	(0.36)	
7. Mean log entrant wage	1.45	1.25	0.20	1.45	1.30	0.15	1.42	1.24	0.18
	(0.54)	(0.56)		(0.54)	(0.49)		(0.59)	(0.54)	
8. Proportion of entrants	0.11	0.14	-0.03	0.12	0.14	-0.02	0.11	0.14	-0.03
	(0.32)	(0.35)		(0.32)	(0.35)		(0.32)	(0.35)	

Figures in parentheses are standard errors

Table 6.4 Accounting for the Gender Pay Gap

	1992			*1993*		
	Men	Women	Gap	Men	Women	Gap
Implied steady-state wage	**1.99**	**1.67**	**0.33**	**1.70**	**1.46**	**0.24**
2. Male entrant share	1.99	1.79	0.20	1.70	1.52	0.18
3. Female entrant share	1.87	1.67	0.21	1.64	1.46	0.18
4. Male log entrant wage	1.99	1.89	0.11	1.70	1.64	0.06
5. Female log entrant wage	1.77	1.67	0.11	1.52	1.46	0.06
6. Male log wage change	1.99	1.67	0.33	1.70	1.42	0.29
7. Female log wage change	1.99	1.67	0.33	1.76	1.46	0.30

Table 6.4 Accounting for the Gender Pay Gap (*cont.*)

	1994			*1995*			*Total*		
	Men	Women	Gap	Men	Women	Gap	Men	Women	Gap
Implied steady-state wage	**1.93**	**1.58**	**0.35**	**1.86**	**1.56**	**0.30**	**1.85**	**1.57**	**0.29**
2. Male entrant share	1.93	1.68	0.25	1.86	1.56	0.30	1.85	1.66	0.19
3. Female entrant share	1.82	1.58	0.24	1.80	1.56	0.23	1.76	1.57	0.19
4. Male log entrant wage	1.93	1.78	0.15	1.86	1.73	0.13	1.85	1.75	0.11
5. Female log entrant wage	1.73	1.58	0.15	1.69	1.56	0.13	1.67	1.57	0.11
6. Male log wage change	1.93	1.61	0.32	1.86	1.56	0.30	1.85	1.55	0.31
7. Female log wage change	1.89	1.58	0.31	1.86	1.56	0.30	1.88	1.57	0.31

Table 6.5 Decomposition of the Full-Time - Part-Time Pay Gap

	1992		*1993*		*1994*		*1995*	
	Full	Part	Full	Part	Full	Part	Full	Part
1. Mean log wage	1.52	1.34	1.54	1.31	1.55	1.33	1.56	1.32
	(0.50)	(0.53)	(0.49)	(0.51)	(0.51)	(0.51)	(0.50)	(0.52)
2. Mean log initial wage	1.50	1.28	1.54	1.33	1.54	1.32	1.54	1.33
	(0.51)	(0.48)	(0.48)	(0.53)	(0.50)	(0.51)	(0.51)	(0.51)
3. Proportion now full-time	0.81	0.07	0.85	0.07	0.84	0.09	0.83	0.08
	(0.39)	(0.25)	(0.36)	(0.25)	(0.37)	(0.29)	(0.37)	(0.27)
4. Mean log wage change for	0.024	-0.089	0.012	-0.113	0.043	-0.129	0.044	-0.110
those now full-time	(0.19)	(0.34)	(0.20)	(0.36)	(0.22)	(0.46)	(0.20)	(0.44)
5. Covariance between initial	0.022	0.022	0.031	0.016	0.022	0.001	0.024	0.016
wage and current FT	(0.74)	(0.44)	(0.71)	(0.42)	(0.72)	(0.36)	(0.74)	(0.45)
employment								
6. Proportion now PT	0.05	0.73	0.04	0.78	0.05	0.73	0.04	0.76
	(0.21)	(0.44)	(0.20)	(0.42)	(0.21)	(0.44)	(0.20)	(0.43)
7. Mean log wage change for	0.238	0.030	0.288	0.011	0.194	-0.000	0.234	0.008
those now PT	(0.50)	(0.32)	(0.51)	(0.33)	(0.41)	(0.33)	(0.46)	(0.30)
8. Covariance between initial	0.003	0.020	-0.011	-0.005	0.002	0.001	-0.007	0.002
wage and current PT	(0.35)	(0.69)	(0.28)	(0.71)	(0.36)	(0.71)	(0.31)	(0.71)
employment								
9. Mean log entrant wage	1.22	1.16	1.22	1.17	1.20	1.21	1.21	1.18
	(0.54)	(0.56)	(0.60)	(0.48)	(0.55)	(0.56)	(0.45)	(0.58)
10. Proportion of entrants	0.10	0.18	0.08	0.21	0.11	0.19	0.09	0.21
	(0.30)	(0.39)	(0.27)	(0.40)	(0.31)	(0.39)	(0.28)	(0.41)
11. Proportion previously FT	0.84	0.06	0.86	0.05	0.82	0.07	0.85	0.06
	(0.36)	(0.24)	(0.34)	(0.22)	(0.38)	(0.25)	(0.36)	(0.24)
12. Proportion previously PT	0.06	0.76	0.05	0.74	0.07	0.74	0.06	0.73
	(0.23)	(0.43)	(0.23)	(0.44)	(0.26)	(0.43)	(0.23)	(0.44)

Note. Standard errors in parentheses.

Table 6.6 Changes in the Entrant Share 1975-1995

Year	*Entrant Share*				
	Male	Female	Gap	Female PT	Female FT
1975	.040	.120	+.08	.160	.096
1981	.048	.105	+.07	.139	.081
1985	.067	.124	+.06	.163	.098
1990	.061	.110	+.05	.156	.079
1995	.073	.108	+.04	.151	.076

Source: LFS

Table 6.7 The Entry and Average Gender Pay Gap 1979-91

Year	*Pay Gap*			
	Gender	FT – PT	Gender Entry	FT - PT Entry
1979	.45	.16	.12	.02
1983	.43	.18	.20	-.16
1985	.42	.21	.03	-.21
1987	.41	.20	.04	-.14
1991	.39	.25	.13	.05

Source. GHS

Table 6.8 Characteristics of the Wage Equation Sample: Men and Women

	Whole sample		*Continuing workers*		*Entrants*	
	men	women	men	women	men	women
Experience (years)	20.6 (12.4)	21.0 (12.4)	20.9 (12.2)	21.4 (12.4)	17.6 (13.4)	18.0 (12.2)
Job tenure (years)	5.52 (6.56)	4.65 (5.29)	5.98 (6.65)	5.08 (5.38)		
Proportion changed jobs in past year	0.21	0.19	0.17	0.17		
Proportion with degree	0.13	0.10	0.14	0.10	0.12	0.09
Proportion with teaching/nursing	0.26	0.21	0.26	0.21	0.23	0.18
'A' level or equivalent	0.16	0.10	0.16	0.10	0.18	0.11
'O' level or equivalent	0.26	0.38	0.26	0.38	0.28	0.40
White	0.97	0.97	0.97	0.97	0.96	0.97
Married	0.67	0.65	0.69	0.65	0.52	0.63
Number of kids aged below 5 in household	0.19 (0.46)	0.12 (0.36)	0.19 (0.46)	0.09 (0.31)	0.18 (0.46)	0.34 (0.57)
Number of kids aged 5-11 in household	0.29 (0.63)	0.29 (0.62)	0.29 (0.64)	0.27 (0.60)	0.29 (0.62)	0.45 (0.73)
Number of kids aged 12-18 in household	0.19 (0.48)	0.22 (0.50)	0.19 (0.48)	0.22 (0.50)	0.20 (0.51)	0.22 (0.51)
Workplace <25 employees	0.27	0.41	0.26	0.39	0.44	0.54
Workplace 25-99 employees	0.26	0.25	0.26	0.26	0.24	0.22
Workplace 99-499 employees	0.28	0.21	0.28	0.21	0.21	0.15
Log wage	1.81 (0.52)	1.45 (0.52)	1.84 (0.50)	1.49 (0.50)	1.46 (0.578)	1.210 (0.54)
Log wage change	-	-	0.019 (0.26)	0.023 (0.28)	-	-
Proportion of entrants	0.09	0.12	0	0	1	1

Note. Standard errors in parentheses.

Table 6.9 Characteristics of the Sample: Full-Time and Part-Time Women

	Whole sample		*Continuing workers*		*Entrants*	
	FT	PT	FT	PT	FT	PT
Experience (years)	18.0 (11.8)	24.8 (11.9)	18.3 (11.8)	25.8 (11.7)	13.6 (11.2)	20.1 (12.0)
Job tenure (years)	4.37 (5.07)	5.00 (5.53)	4.62 (5.13)	5.73 (5.53)		
Proportion changed jobs in past year	0.23	0.15	0.20	0.12		
Proportion with degree	0.12	0.06	0.12	0.06	0.11	0.07
Proportion with teaching/nursing	0.25	0.17	0.25	0.17	0.24	0.17
'A' level or equivalent	0.12	0.08	0.12	0.08	0.15	0.10
'O' level or equivalent	0.37	0.40	0.37	0.39	0.36	0.41
White	0.97	0.98	0.97	0.98	0.96	0.97
Married	0.53	0.80	0.54	0.81	0.43	0.74
Number of kids aged below 5 in household	0.07 (0.28)	0.18 (0.44)	0.06 (0.25)	0.13 (0.38)	0.24 (0.49)	0.39 (0.60)
Number of kids aged 5-11 in household	0.14 (0.43)	0.48 (0.76)	0.13 (0.42)	0.46 (0.75)	0.23 (0.50)	0.56 (0.80)
Number of kids aged 12-18 in household	0.15 (0.43)	0.29 (0.57)	0.15 (0.43)	0.31 (0.58)	0.20 (0.52)	0.23 (0.50)
Workplace <25 employees	0.30	0.53	0.30	0.51	0.37	0.61
Workplace 25-99 employees	0.27	0.23	0.27	0.24	0.24	0.21
Workplace 99-499 employees	0.25	0.16	0.25	0.16	0.23	0.12
Log wage	1.56 (0.49)	1.32 (0.52)	1.58 (0.48)	1.36 (0.51)	1.27 (0.54)	1.18 (0.53)
Proportion of entrants	0.07	0.18	0	0	1	1

Note. Standard errors in parentheses.

Table 6.10 Traditional Wage Equations

Variable	*All*	*Men*	*Women*	*FT women*	*PT women*
Constant	0.77*	0.82*	0.78	0.73	1.16*
	(0.04)	(0.06)	(0.06)	(0.08)	(0.10)
Experience (years/10)	0.87*	0.88*	0.88*	0.97*	0.48*
	(0.05)	(0.07)	(0.07)	(0.09)	(0.15)
Experience squared $(years/10)^2$	-0.43*	-0.42*	-0.44*	-0.47*	-0.26*
	(0.04)	(0.05)	(0.05)	(0.07)	(0.09)
Experience cubed $(years/10)^3$	0.086*	0.091*	0.083*	0.093*	0.055*
	(0.010)	(0.013)	(0.014)	(0.022)	(0.024)
Experience quartic $(years/10)^4$	-0.007*	-0.0076*	-0.006*	-0.007*	-0.004*
	(0.001)	(0.0011)	(0.0013)	(0.0022)	(0.0020)
Job tenure (years/10)	0.15*	0.07*	0.18*	0.14*	0.19*
	(0.017)	(0.022)	(0.026)	(0.034)	(0.040)
Job tenure $(years/10)^2$	-0.025*	-0.011	-0.053*	-0.057*	-0.039*
	(0.006)	(0.007)	(0.010)	(0.010)	(0.016)
Job changer	0.040*	-0.002	0.047*	0.021	0.056*
	(0.011)	(0.014)	(0.014)	(0.017)	(0.024)
Degree-holder	0.83*	0.74*	0.84*	0.82*	0.87*
	(0.015)	(0.019)	(0.020)	(0.026)	(0.035)
Teaching/nursing qualification	0.47*	0.41*	0.46*	0.44*	0.45*
	(0.012)	(0.016)	(0.016)	(0.022)	(0.025)
'A' level or equivalent	0.35*	0.28*	0.28*	0.28*	0.26*
	(0.013)	(0.017)	(0.019)	(0.025)	(0.032)
'O' level or equivalent	0.17*	0.20*	0.17*	0.18*	0.14*
	(0.011)	(0.016)	(0.014)	(0.020)	(0.020)
White	0.11*	0.12*	0.11*	0.15*	0.04
	(0.02)	(0.03)	(0.03)	(0.04)	(0.05)
Married	0.07*	0.11*	0.03*	0.036*	0.062*
	(0.01)	(0.013)	(0.01)	(0.013)	(0.020)
Number of kids aged below 5 in household	0.030*	0.026*	-0.039*	-0.022	0.010
	(0.009)	(0.012)	(0.014)	(0.022)	(0.021)
Number of kids aged 5-11 in household	-0.044*	-0.002	-0.102*	-0.087*	-0.051*
	(0.006)	(0.008)	(0.008)	(0.014)	(0.012)
Number of kids aged 12-18 in household	-0.016*	0.008	-0.040*	-0.068*	0.015
	(0.008)	(0.011)	(0.010)	(0.014)	(0.015)
Workplace <25 employees	-0.34*	-0.27*	-0.29*	-0.26*	-0.29*
	(0.011)	(0.015)	(0.015)	(0.018)	(0.028)
Workplace 25-99 employees	-0.15*	-0.11*	-0.14*	-0.13*	-0.12*
	(0.011)	(0.015)	(0.016)	(0.018)	(0.031)
Workplace 99-499 employees	-0.06*	-0.06*	-0.06*	-0.06*	-0.06
	(0.011)	(0.015)	(0.016)	(0.018)	(0.032)
Number of observations	14559	7020	7539	4180	3359
R^2	0.37	0.37	0.38	0.42	0.31

Notes.1. Regional dummies and wave dummies were also included but these results are not reported.
2. Standard errors in parentheses. 3. Dependent Variable: Log Wage. 4. Sample: All Workers.
5. Asterisk notes significance at 5% level.

Table 6.11 Wage Growth Equations

Variable	*All*	*Men*	*Women*	*FT women*	*PT women*
Constant	0.10*	0.13*	0.06	0.06	0.15
	(0.03)	(0.04)	(0.04)	(0.05)	(0.09)
Experience (years/10)	-0.13*	-0.19*	-0.050*	-0.006	-0.131
	(0.04)	(0.05)	(0.005)	(0.058)	(0.139)
Experience squared $(years/10)^2$	0.063*	0.098*	0.011	-0.051	0.057
	(0.025)	(0.034)	(0.04)	(0.04)	(0.09)
Experience cubed $(years/10)^3$	-0.013	-0.022*	0.003	0.024	-0.012
	(0.007)	(0.009)	(0.011)	(0.014)	(0.023)
Experience quartic $(years/10)^4$	0.010	0.017*	-0.003	-0.003	-0.0009
	(0.006)	(0.008)	(0.010)	(0.0014)	(0.002)
Job tenure (years/10)	-0.007	0.002	-0.017	-0.026	-0.016
	(0.011)	(0.001)	(0.019)	(0.021)	(0.003)
Job tenure $(years/10)^2$	0.001	-0.001	0.004	0.010	0.005
	(0.004)	(0.004)	(0.007)	(0.008)	(0.014)
Job changer	0.020*	0.028*	0.013	0.017	0.007
	(0.007)	(0.010)	(0.011)	(0.011)	(0.023)
Degree-holder	0.016	0.014	0.028	0.017	0.079
	(0.010)	(0.013)	(0.015)	(0.016)	(0.030)
Teaching/nursing qualification	0.008	0.010	0.013	0.017	0.017
	(0.008)	(0.011)	(0.012)	(0.014)	(0.021)
'A' level or equivalent	0.011	0.013	0.019	0.022	0.030
	(0.009)	(0.012)	(0.014)	(0.016)	(0.028)
'O' level or equivalent	0.013	0.021	0.0098	0.025*	-0.000
	(0.007)	(0.011)	(0.010)	(0.012)	(0.016)
White	0.004	0.004	0.011	0.031	-0.030
	(0.014)	(0.020)	(0.022)	(0.022)	(0.045)
Married	-0.006	-0.016	0.002	-0.010	0.013
	(0.006)	(0.0088)	(0.008)	(0.008)	(0.017)
Number of kids aged below 5 in household	0.0046	0.0075	0.0042	0.012	-0.018
	(0.006)	(0.008)	(0.011)	(0.015)	(0.020)
Number of kids aged 5-11 in household	-0.0041	-0.0012	-0.0048	-0.0035	-0.016
	(0.004)	(0.006)	(0.006)	(0.009)	(0.011)
Number of kids aged 12-18 in household	0.0073	0.0023	0.012	-0.003	0.017
	(0.005)	(0.007)	(0.007)	(0.009)	(0.013)
Workplace <25 employees	-0.005	-0.0063	-0.0049	-0.0086	-0.019
	(0.007)	(0.010)	(0.011)	(0.011)	(0.024)
Workplace 25-99 employees	-0.004	-0.0099	-0.0001	-0.0048	-0.0069
	(0.007)	(0.010)	(0.011)	(0.011)	(0.026)
Workplace 99-499 employees	-0.001	-0.013	0.014	0.012	0.007
	(0.007)	(0.010)	(0.011)	(0.011)	(0.027)
Number of observations	13005	6386	6619	3880	2739
R^2	0.01	0.02	0.01	0.02	0.02

Notes. 1.Regional dummies and wave dummies were also included but these results are not reported. 2. Standard errors in parentheses. 3 Dependent Variable: Change in Log Wage. 4. Sample: Workers in Continuous Employment. 5. Asterisk notes significance at 5% level.

Table 6.12 Entrant Wage Equations

Variable	*All*	*Men*	*Women*	*FT women*	*PT women*
Constant	1.17*	0.96*	0.84*	0.57*	1.01*
	(0.13)	(0.20)	(0.19)	(0.27)	(0.25)
Experience	0.69*	0.49*	0.82*	1.59*	0.09
(years/10)	(0.14)	(0.21)	(0.02)	(0.03)	(0.30)
Experience squared	-0.33*	-0.14	-0.46*	-1.10*	-0.02
$(years/10)^2$	(0.11)	(0.16)	(0.14)	(0.31)	(0.20)
Experience cubed	0.07*	0.016	0.100*	0.298*	0.006
$(years/10)^3$	(0.03)	(0.042)	(0.039)	(0.102)	(0.051)
Experience quartic	-0.0051*	-0.0011	-0.007*	-0.028*	-0.000
$(years/10)^4$	(0.0025)	(0.0037)	(0.003)	(0.011)	(0.004)
Degree-holder	0.67*	0.61*	0.70*	0.70*	0.76*
	(0.05)	(0.08)	(0.07)	(0.12)	(0.09)
Teaching/nursing qualification	0.37*	0.30*	0.39*	0.41*	0.43*
	(0.04)	(0.06)	(0.05)	(0.10)	(0.07)
'A' level or equivalent	0.31*	0.27*	0.32*	0.47*	0.24*
	(0.04)	(0.07)	(0.06)	(0.11)	(0.08)
'O' level or equivalent	0.17*	0.14*	0.17*	0.23*	0.16*
	(0.04)	(0.06)	(0.04)	(0.09)	(0.05)
White	0.052	0.16	-0.011*	-0.099	0.009
	(0.069)	(0.11)	(0.090)	(0.151)	(0.116)
Married	0.059	0.092	0.035	0.027	0.043
	(0.031)	(0.052)	(0.038)	(0.064)	(0.049)
Number of kids aged below 5 in household	0.064*	0.075	0.046	0.104	0.060
	(0.026)	(0.046)	(0.033)	(0.065)	(0.041)
Number of kids aged 5-11 in household	-0.066*	-0.062	-0.075*	-0.093	-0.035
	(0.020)	(0.035)	(0.024)	(0.056)	(0.029)
Number of kids aged 12-18 in household	-0.046	-0.072	-0.024	-0.018	-0.017
	(0.026)	(0.042)	(0.033)	(0.058)	(0.041)
Workplace <25 employees	-0.33*	-0.32*	-0.30*	-0.30*	-0.25*
	(0.04)	(0.07)	(0.05)	(0.08)	(0.08)
Workplace 25-99 employees	-0.18*	-0.21*	-0.12*	-0.12	-0.06
	(0.05)	(0.07)	(0.06)	(0.09)	(0.09)
Workplace 99-499 employees	-0.07	-0.12	-0.01	-0.11	0.11
	(0.05)	(0.08)	(0.06)	(0.09)	(0.10)
Number of observations	1554	634	920	300	620
R^2	0.30	0.29	0.28	0.42	0.27

Note. 1. Standard errors in parentheses. 2. Dependent Variable: Log Wage. 3. Sample: Entrant Workers. 4. Asterisk notes significance at 5% level.

Table 6.13 Entrant Equations Dependent Variable: Entrant Dummy

Variable	*All*	*Men*	*Women*	*FT women*	*PT women*
Constant	0.31*	0.32*	0.26*	0.28*	0.40*
	(0.03)	(0.04)	(0.04)	(0.05)	(0.09)
Experience	-0.33*	-0.38*	-0.33*	-0.45*	-0.24*
(years/10)	(0.04)	(0.05)	(0.05)	(0.06)	(0.12)
Experience squared	0.18*	0.22*	0.20*	0.30*	0.09
$(years/10)^2$	(0.02)	(0.03)	(0.04)	(0.05)	(0.08)
Experience cubed	-0.044*	-0.05	-0.049*	-0.081*	-0.020
$(years/10)^3$	(0.007)	(0.009)	(0.010)	(0.014)	(0.020)
Experience quartic	-0.0036*	-0.004*	-0.004*	-0.007*	0.002
$(years/10)^4$	(0.0006)	(0.0008)	(0.001)	(0.001)	(0.002)
Degree-holder	-0.060*	-0.040*	-0.069*	-0.054*	-0.071*
	(0.010)	(0.013)	(0.015)	(0.017)	(0.029)
Teaching/nursing qualification	-0.043*	-0.024*	-0.054*	-0.039*	-0.049*
	(0.008)	(0.011)	(0.012)	(0.015)	(0.021)
'A' level or equivalent	-0.028*	-0.009	-0.045*	-0.027	-0.046
	(0.009)	(0.012)	(0.015)	(0.017)	(0.027)
'O' level or equivalent	-0.030*	-0.021	-0.042*	-0.033*	-0.041*
	(0.008)	(0.011)	(0.010)	(0.013)	(0.017)
White	-0.028*	-0.024	-0.037	-0.005	-0.065
	(0.015)	(0.020)	(0.022)	(0.024)	(0.043)
Married	-0.029*	-0.033*	-0.022*	-0.023*	-0.054*
	(0.006)	(0.009)	(0.008)	(0.008)	(0.017)
Number of kids aged below 5 in household	0.089	0.014	0.215*	0.171*	0.170*
	(0.006)	(0.008)	(0.011)	(0.014)	(0.018)
Number of kids aged 5-11 in household	0.034*	0.016*	0.053*	0.040*	0.018
	(0.004)	(0.006)	(0.006)	(0.009)	(0.010)
Number of kids aged 12-18 in household	0.015*	0.014*	0.013	0.023*	-0.011
	(0.005)	(0.007)	(0.008)	(0.009)	(0.013)
Workplace <25 employees	0.081*	0.081*	0.072*	0.017	0.090*
	(0.008)	(0.010)	(0.011)	(0.012)	(0.024)
Workplace 25-99 employees	0.026*	0.027*	0.022	0.000	0.036
	(0.008)	(0.010)	(0.012)	(0.012)	(0.026)
Workplace 99-499 employees	0.007	0.013	0.002	0.000	-0.004
	(0.008)	(0.007)	(0.013)	(0.012)	(0.028)
Number of observations	14561	7021	7540	4180	3360
R^2	0.048	0.044	0.089	0.069	0.099

Note. 1. Standard errors in parentheses. 2. Sample: All Workers. 3. Asterisk notes significance at 5% level.

Table 6.14 Chow Tests and Oaxaca Decompositions

A. Men versus Women

	Chow test for equality of coefficients	*Raw Differential*	*Oaxaca Decompositions*			
			Female Characteristics		Male characteristics	
			coefficients	Characteristics	coefficients	characteristics
1. log wage	42.3 (40,14520)	0.36	0.28	0.08	0.27	0.09
2. log wage change	0.98 (40, 12966)	-0.0040	-0.0036	-0.0004	-0.0072	0.0032
3. entry log wage	3.09 (37,1518)	0.25	0.24	0.01	0.21	0.04
4. entrant proportion	10.07 (37,14525)	-0.031	-0.021	-0.010	-0.033	0.002

B. FT versus PT Women

	Chow test for equality of coefficients	*Raw Differential*	*Oaxaca Decompositions*			
			PT Characteristics		FT characteristics	
			Coefficients	Characteristics	coefficients	characteristics
1. log wage	5.77 (40,7500)	0.24	0.09	0.15	0.10	0.14
2. log wage change	2.06 (40, 6580)	-0.0105	-0.0362	0.0257	-0.0415	0.0310
3. entry log wage	1.51 (37,884)	0.09	-0.025	0.112	-0.016	0.104
4. entrant proportion	5.80 (37,7504)	-0.113	-0.083	-0.029	-0.115	0.002

Figures in parentheses are F test degrees of freedom.

Chapter 7

An Analysis of Career breaks, Fertility and Women Returners: Modelling the Length of Withdrawal and Subsequent Return

7.1 Introduction

The evidence presented so far in this thesis, suggests that much of the wage gap observed between men and women, and between different groups of women, stems from the length of labour market withdrawal and the subsequent low wages on re-entry. In general, the longer the time spent out of work, the heavier the wage penalty. The previous Chapters have looked at the wage determination process in some detail. This Chapter now focuses on the principle features of the duration of time out and the nature of the subsequent re-entry, in order to establish the principle factors determining the length of time out.

The study of the rise in female labour force participation in western economies has been a central research area for over two decades (see amongst others Mincer (1962), Joshi, Layard and Owen (1985) and Goldin (1997)). Chapter 2 has shown that the employment rate for women grew by 9 percentage points between 1981 and 1991. One key aspect of this development is that women are engaging in work in households already supported by other working members (see, for example, Gregg and Wadsworth (1996) and Davies, Joshi and Peronaci (1998)). The proportion of married or cohabiting couples where both partners are in work has risen from 43 per cent in 1975 to 60 per cent in 1992 (Gregg and Wadsworth (1996)). Moreover, as illustrated in Chapter 2, the increase in employment rates has been highest for women with young children. Whilst rising female participation undoubtedly contributes to rising household income and a rising share of total household income, (Harkness, Machin and Waldfogel (1995)), there remains some tension between the roles of women in formal work and in the unpaid rearing of children. Given the combination of these duties, how do women allocate themselves across full-time work, part-time work or no work, and how does this vary across women?

The introduction of statutory maternity leave in 1979 facilitated the maintenance of a foothold in the world of work. However, the law as it stands guarantees only a right to return to the previous job and not the right to move from full to part-time work (which remains at the discretion of the employer). For women who wish to combine child care and formal work, a change of employer may be the only option. Moreover, extended leave rights are only available to those satisfying a minimum length of service, (currently 2 years). The amount of maternity pay is also conditional on length of service and earnings. As such, the opportunity costs of returning to work (either full- or part-time) will differ across the population, irrespective of partner's status (if a partner is present).

Whilst some literature exists on the economic fortunes of women on subsequent re-entry, (which Chapters 4 and 5 extend), less attention has been given to analysing the duration structure of childcare spells. This Chapter quantifies to what extent the route back into work differs for a cohort of British mothers and examines the determinants of the process of returning to work using information from the National Child Development Study (NCDS). Since the NCDS encourages mothers to include maternity leave as part of a continuous spell of employment, we concentrate on those women who have taken time out of work over and above that considered by respondents to be normal maternity leave. These women can be considered as having a more marginal labour force attachment. The choice between returning to the workplace on a full- or part-time basis in the presence of children will be influenced (as outlined in Chapter 5), by the presence of a partner (or support networks) and the nature and the location of the previous job. This Chapter quantifies the importance of these factors in the return to work. We use Markovian transition matrices to outline the basic movements into and out of childcare. We find that the probability of returning to part-time work relative to full-time work increases with the age at which women return to work. Probit regressions confirm that the age of young children in the household play a pivotal part in this process. The Chapter then proceeds to use survival analysis to examine the length of spells of childcare when the exit routes differ and to investigate the determinants of the lengths of time out.

7.2 Introduction to the Previous Literature

Recent Work

Within the public arena, the overriding view is that, although the activities associated with the birth and raising of children are crucial to societal stability, there needs to be an underlying process which encourages women back into work following the advent of motherhood. Why should this be so? The answer most often provided by policy analysts is that some groups of mothers, especially those who are single heads of households, may remain outside formal work for several years in the absence of suitable pressure for them to re-enter the labour force. The empirical link between lone motherhood, unemployment and poverty is so well established (see Bryson, Ford and White (1998) for recent evidence) that the common held view is that a return to paid work, and thereby a move off state benefits, provides an escape from this process. Indeed recent government policy initiatives (the introduction of the Working Family Tax Credit, for example) are in line with this view. Further, there exists pressure for women in dual income households to remain in work after a break for childrearing. The quicker women return to work following a gap, the less likely it is that a break adversely affects earnings through the loss of valuable work experience. Also, the less likely it is that there will be a substantial re-entry penalty in the manner documented in Chapter 5.

Here, we analyse whether female spells of childcare are different when the exit routes differ. We think of work as divided into part- and full-time states. According to Blank (1989), female labour market activity in the United States comprises essentially two groups of female workers. The first crudely consists of mainly continuous, full-time workers, who interrupt their labour market experience minimally in order to have children and who then return to the labour market as soon as possible. The second group is seen to have less involvement in the world of work and members drop out of the labour force for between three and five years upon the birth of the first child. These women subsequently return to the labour market on a part-time basis, combining formal work with child-rearing. This latter group is behaviourally quite different from the first group. This Chapter tries to assess the validity of this hypothesis for the latter group of women in Britain. Can it be said that women who take more time out are more likely to return to work on a part-time basis?

Chapter 2 showed that, despite recent changes, part-time work is still taken up by the majority of women with young children. Does part-time work form merely a brief stage in the move to more secure full-time work? Blank (1989) uses the US Panel Study of Income Dynamics data and a competing risks framework to analyse the stepping stone view of part-time work. Blank's findings do not support the hypothesis that women use part-time work as a bridge between non-work and full-time work. Although it is found that part-time work spells are more likely to end than spells of non-work or full-time work, part-time work is just as likely to generate an exit into non-work as it is to produce an exit into full-time work. The determinants of spell length vary across labour market states and most women are seen to have a high degree of inertia with respect to change from the current state in which they are found. Blank finds that over three-quarters of her sample of women remain for the most part in the same labour market state over a nine-year period, which is indicative of a large amount of inertia. Similarly, Giannelli (1996) shows that, for women in Germany, the length of spells of part- and full-time work is very similar. Moreover, as in the United States, part-time work in Germany does not appear to be a step towards full-time employment.

As yet, there is little evidence whether this dichotomy holds in Britain. In this Chapter, we are able to study women who return to either full- or part-time work, along with their marital, fertility and employment histories. We are in a position to assess whether simple family characteristics, such as the age and presence of children in the household, the opportunity cost of not being in work (as measured by a potential wage variable) and the household income overshadows other effects such as the age and level of educational attainment of women in the process of returning to work. If the two groups of women are essentially distinct, then a policy that encourages low paid part-time workers into full-time work as a means of increasing job security is misplaced. Rather, attention should be given to ensuring part-time work carries the same rights and conditions as does full-time work.

To begin to analyse these issues further, this Chapter seeks to understand fully the dynamic choices of the group of women with a more marginal attachment to the labour force. We incorporate information on the preferences and employment history of women who take more than the statutory minimum maternity leave after child birth to

examine the dynamics of transitions back to work, focusing on the distinction between re-entry to full- and part-time work. Our sample of data allows us to analyse precisely the characteristics of these women and the pattern of transitions back into work that they subsequently make. As we are primarily interested in those women who have a more marginal attachment to the labour market, we exclude women who have taken statutory maternity leave, as these are grouped in the NCDS data along with continuous female workers.

Some complementary evidence of this for Britain may be found in Ermisch and Wright (1991 (b)). Using the 1980 Women and Employment Survey, they find that married women with comparatively lower observed skills and other human capital characteristics are much more likely to be employed part-time. According to the authors, these women select themselves into part-time jobs that have associated lower wages. Although as we have shown, Chapter Five offers a different explanation for the full-time - part-time wage gap.

If the undertaking of part-time work is not a transitional phase, are we able to categorise the workers who occupy this state? Tables 2.6 and 2.7 of Chapter 2 demonstrate the trend of part-time work to be more associated with older women and young workers. Part-time work is not uniquely associated the mothers of young children perhaps using it as a stepping-stone into full-time work. One important feature of British part-time work is that some 87.3 per cent of part-time jobs were held by women at the end of our sample period (Labour Force Survey (1991)). Some 50.2 per cent of part-time jobs were held by mothers (*ibid*). The studies which have highlighted differences between the labour market behaviour of mothers and non-mothers, and full-timers and part-timers, have usually been based upon cross-sectional data (for example, Levine and Moock (1984), and Groot, Schippers and Siegers (1990)). The NCDS data set, which we use in this Chapter, provides us with the opportunity to perform a far richer analysis of the dynamics of female labour force participation, as we have the comprehensive retrospective work histories for all cohort members. Much of the previous work suggests an increase in the probability of entry to full-time employment for mothers as the age of the youngest child increases (see Ermisch and Wright (1991 (b)), as an example).

Joshi, Macran and Dex (1996) also document the increased attachment to the labour force of the 1958 NCDS cohort of British mothers. When NCDS mothers reached the age of 33 in 1991, they were among the first generation of women to enjoy statutory maternity leave. In stark contrast to other European countries, British women have been noted for their intermittent participation in the labour market (perhaps due to inadequate provision of childcare). Dex et al (1993), for example, gives evidence of the less marginal attachment of French women. Gaps in female employment in Britain have historically been linked to the birth of the first child. Dex has also found that the subsequent return to work has been characterised by various part-time posts. Nakamura and Nakamura (1994) show that in the US and in Canada, the effect of children on female participation is reduced when controlling for previous labour market experience.

Joshi, Macran and Dex (1996) draw upon their depth of knowledge about female labour force participation acquired through previous work using the Medical Research Council (MRC) data on a birth cohort of 1946 (Joshi and Hinde (1993)). Females born in the NCDS cohort (twelve years after the MRC cohort) had a much higher propensity to minimise on their time away from the formal labour market following childbirth. However, within this changing framework, socially differentiable patterns of participation are distinguishable. More specifically, it would seem that for the 1958 cohort, the attachment of highly qualified, middle class mothers to the labour force was reaching levels hitherto only observed in countries such as France. Joshi *et al* use a multinomial model to predict the probability of being in full-time or part-time work. This analysis includes the calculation of an imputed wage for some 723 women (of the 3597 women) for whom a market wage was not observable. (This information was missing for women not employed at the time of the last interview or for those who did not report the information.)[1] The explanatory variables include childbearing history, partnership history, partner's income, housing type, imputed earning power, social attitudes, health and employment patterns. The majority of NCDS women without children were engaged in full-time employment (86 per cent) whilst those with pre-nursery children were more likely to be outside the labour force (53 per cent). In line

[1] Here, the log wage was generated from a regression of the total years of work experience, an ability score attained at seven years, a living in the south east dummy and educational qualifications.

with previous work (Joshi (1994)), partnership history was included in the analysis, as females in less long-term relationships have been found to be more likely to be engaged in formal paid work. Joshi *et al* find that when children are of primary school age, females have positive probabilities of being in part-time employment. Further, women have a higher probability of being employed full-time if they are in a relationship with a partner who is not their first. There is a clear, positive association of the probability of being employed either full- or part-time if a female chooses not to have a gap in employment upon the birth of her first child or if that gap is of less than nine months. The NCDS data set provides detailed information on cohort members' attitudes to various social phenomena. Joshi *et al* (1996) select two questions which indicate beliefs known to impact upon the probability of an individual participating in the labour market. These attitudes were ranked out of five indicating strong agreement through to strong disagreement. On average, those women who were sceptical about equal opportunities issues at the age of 23 were found to be amongst those in the full-time and so-called better jobs at the age of 33.

One way of viewing the results of this work is in terms of simulated probabilities for chosen cases. Joshi *et al* use the example of a married woman who has mean values for all continuous regressors and who belongs to the default category for all others. Such a woman's predicted participation rate of being in full-time work, should she be childless, would be .79. However, if she had one child aged less than 3, her predicted probability of being in full-time work would be .39. Her predicted probability of being in part-time work would be .29. A woman with two children (the youngest of which is in the 5 - 10 year age band) would have a predicted probability of being in part-time work of .57. Joshi *et al* conclude that their work provides additional support for the observation that there is increased polarisation in the labour market. Their evidence suggests that females characterised by short maternity breaks and full-time employment records have low probabilities of being subsequently found in part-time work. However, females living in social housing with a partner in receipt of means-tested state benefits have a low probability of being in either full- or part-time employment. Such elongated withdrawal from the labour market results in further human capital depreciation and mechanisms, which reinforce their separation from full-time work. Such depreciation and negative impact of withdrawal on wages were discussed at length in Chapter Five.

In what follows, we extend the work of Joshi *et al*, using the same data set, but by modelling the transition process explicitly using continuous time analyses and, more importantly, tracking the relative entry rates in to full- and part-time work as the cohort ages. We provide evidence of the differences in the labour market attachment of women given the age at which the various labour market states are occupied. The first half of this Chapter investigates the transitions into and out of different labour market states for NCDS women and how these evolve between the ages of 23 and 33 years. We then develop the study to include the specific modelling of the duration of the childcare spell whilst controlling for other observable characteristics. We also assess the impact of these various characteristics. We show that the chances of returning to part-time work relative to full-time work increase with the age at which women return to work. This process is heavily influenced by the age of the youngest child in the household unit.

Other Developments

The pattern of female labour force participation changed dramatically over our sample period. In Britain, more women in the 25-45 age group are to be found economically active than ever before. However, significant numbers of women still experience discontinuities in their employment history at the time of childbirth (see evidence in Chapter 2). During this time period, real wages have increased (see Chapter 2 for Britain, and Juhn and Murphy (1996) for the United States). This has made the opportunity to stay at home throughout the childbearing period an affordable option for large numbers of women, thereby reducing female labour supply. However, this negative income effect on supply has been offset through the substitution effect of an increase in the opportunity costs of female non-participation. Additionally, an increase in real female wages has made the purchase of quality childcare affordable for some groups of women, thereby offsetting a substantial fixed cost of labour supply. Given an expansion in post-war female job possibilities, the proportion of female entrants to the labour market has also risen. An increase in job opportunities has occurred alongside an increase in educational possibilities for women and these have been subsequently rewarded in the market. Medical advances have led to far greater female control over fertility. Technological progress has seen the advent of a huge array of labour saving

devices in the typical household. These factors, too, may have led to increases in the labour supply of women.

The applied economic literature on participation in this field falls roughly into two groups. First, that which adopts the structural dynamic programming approach, (see Wolpin (1987)) which seeks to model the complexities of employment behaviour in a life-cycle context. A common feature of the first approach is to model female participation across multiple labour market states in the context of maximising an inter-temporal utility function, which incorporates state dependence.[2] The solution to the optimisation problem is obtained by dynamic programming techniques. This structural form approach is not what we follow here, although we acknowledge the work of authors in this area, such as Francesconi (1995), as having made much progress, partly as a by-product of the recent advances in computing power.

Instead, rather than rely on explicit parameterisation of labour market choices, we adopt a reduced-form approach. We investigate the duration of time spent in the home using models developed with convenient forms with which to estimate transition hazard rates, (see Lancaster (1990), for a survey of these techniques). We develop our analysis by allowing for the possibility of multiple exit states within this reduced-form approach in the second part of this Chapter. A woman may enter any one of a number of labour force states upon the termination of a childcare spell, thus a competing risks framework is appropriate here. After the choice of hazard function is made, the probability of a female spending any particular amount of time in any labour market state is estimated.

As stated in Chapter 1, this thesis is primarily about the labour market fortunes of women. The justification for the focus in this Chapter arises from the feature that women show a higher propensity to move between labour market states than men and that they exhibit a greater range of labour supply choices than have traditionally been associated with men. In what follows, we concentrate solely on our sample of women and focus principally on those women who have spent time engaged in the home. The instructions in the collection of the NCDS data state that women who have taken

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[2] Blank (1989) amongst others, find positive state dependence: that is, women who participate in the labour market at one age are more likely to participate at subsequent ages.

statutory maternity leave are not to indicate this as a break from continuous employment. Those who are on maternity leave should be classed as continuously employed and not as returners.

7.3 Work Experience Profiles

The evidence in Chapter 2 shows that women, especially older and younger women, use part-time work as an alternative to full-time work. Women may then become locked into part-time work. Conversely, the view that women use part-time work as a stepping stone into a full-time job has not been well explored in Britain. This section analyses in some detail the transition profiles for our sample of women.

Breaks in continuous full- or part-time work might be viewed as a profitable phenomenon if women are using their time out of the labour force to review their career paths and to make informed labour market decisions. If workers re-enter the labour force from childcare on a part-time basis at a lower wage and continue to take time to search for a better paid job, then switching between labour force states is consistent with a well-functioning labour market. However, the evidence of Blank cited above suggests that this is not the case in the US. This section looks at the transitions in to work for our sample of British women in more detail. The duration of time spent out of the labour force in childcare (hereafter, CC) was shown to have an important negative effect on wages in Chapter Five.

7.3.1 Labour Market Flows

We begin by summarising the pattern of labour market dynamics amongst the cohort by analysing the various transitions women make in between the years 1981 to 1991 for which we have NCDS information. The cohort member interview and questionnaire in Sweep 5 of the NCDS was designed to obtain in-depth information about both the individual's and their partner's jobs, unemployment, education and training, qualifications, cohabitation, children, housing, health, income and citizenship. By cross-referencing each individual's account of in-work and not-in-a-job dates obtained from the questionnaire, we have built up a month by month account of the work history for each woman who indicated a spell of childcare or domestic duties.

When considering the transitions in and out of a period of childcare, it is important to assess the whole range of exit states. The NCDS questionnaire provides the opportunity to record up to five possibilities for non-work activity. These cover the categories of unemployment, training, full-time education, full-time childcare or housework, and sickness or handicap. Annual outflow rates from childcare into unemployment, training, education and sickness were on average 0.003, 0.001, 0.001 and 0.0002 respectively over the sample period. Due to these relatively small number of transitions, we combine these states into one state (OTHER) to be analysed alongside full-time (FT) or part-time (PT) employment. Participation in work is defined as part-time in the NCDS if it represents employment of less than 30 hours a week. Some of the survey information was unfortunately incomplete for this question. For example, where an individual worked but was unable to disclose whether she was part- or full-time, we class these answers as missing. In addition to the data on monthly labour market status, we use information on household composition, marital status, educational attainment and demographic characteristics to analyse the differences in transitions between non-work, and full-time and part-time work for different age groups of women. This then permits a study of the post-childcare period of re-entry into either full- or part-time work or one of the other activities discussed above. In this section, we present evidence on this in both graphical and tabular form.

We select those mothers who have taken at least one childcare break between the years of 1981 and 1991. This represents an age range from 23 to 33 years of age. With eleven years of data, ten cross-year comparisons can be made. From this group of 2510 women, we retain the information on the labour market state from which they exited and the state to which they return after a break. For this reason, we do not include women for whom we do not have information on activity type before their childcare break. The sample does, however, include those women who have completed a childcare spell and those for whom a spell is still in progress. Over the entire sample period, 1419 women re-enter to a part-time job whilst 353 return to full-time employment, leaving 738 women with incomplete spells. Due to the nature of the NCDS data set, all these censored spells are for women aged thirty-three.

To begin, we summarise the dynamic history by looking at labour market states occupied in the life-cycle twelve months apart, leaving monthly transitions to the survival analysis that follows. We construct simple one-year Markovian transition matrices in the fashion of, amongst many others, Clark and Summers (1979). Here, the probability of subsequent movement depends only on the labour market states currently occupied.

We calculate the annual transition probability, p_{ij}, of moving from state i to state j as $p_{ij} = f_{ij} / s_i$, the number of women in state i and then in state j twelve months later (f_{ij}), divided by the stock of women in state i initially (s_i). This, of course, ignores any "round-tripping" (the moves out of and back into a state) that occur within the 12-month windows. We identify four labour market states: childcare, other out, full-time work and part-time work. Four states yields 16 annual transition probabilities each year, which we use to construct a transition matrix of flow probabilities between states.

Table 7.1 gives the annual transition probabilities out of childcare. Figure 7.1 traces the annual transition probabilities out of childcare and into either full- or part-time work or the other states as the cohort ages. The overall annual outflow rate out of childcare is around 9.4 per cent for women when the cohort is aged 23. This rises as the cohort of women ages to around 20 per cent at age 31 and fall back slightly to 17 per cent at age 33.[3] Outflows are dominated by flows into part-time work. The outflow to part-time work rises by around 250 per cent over the sample period as the cohort ages. When women are between the ages of 21 and 23, the annual transition probability is 6 per cent. By the end of the sample period when the women returners are 33, the transition probability into part-time work is around 15 per cent. In contrast, the outflow rates into full-time work do not appear to vary systematically with age, remaining constant at around 3 per cent. That is, as women get older the relative likelihood of returning to part-time, rather than full-time work, increases.

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[3] Since the transitions are proportions, then the standard errors on the transition rates in any year can be obtained from the formula $\sqrt{(p_{ij} (1 - p_{ij}) / s_i}$. For example, the average standard error for a 5 per cent outflow rate is around 1.4 percentage points.

Table 7.2 outlines the entire matrix of transition probabilities between the four labour market states for years at the start, middle and end of the sample period: 1981-82, 1985-86 and 1990-91, together with the average annual transition matrix over the 10 year window. This is for the entire sample of women with information on labour force status in March of each year, (around 5000 in each year). On average, there is a great deal of stability in labour market behaviour across years. Over 75 per cent of women remain in the same labour market state over the time period. Around 7 per cent of women leave and enter the labour market each year.[4] However, the individual year matrices show that the pattern of labour market flows do change as our sample of women age. The matrices indicate that employment becomes more stable over this time period (the probability of remaining in either full- or part-time work rises over time), which is consistent with the rise in employment rates documented in Chapter 2. The PT to PT probability rises from .8 to .9 over the period despite the advent of the recession in the early 1990's.[5] The FT to FT probability rises by only 3 percentage points.

On average, the inflow rate into child care is around 15 per cent of the population of women in childcare over the 10 year window. The inflow rate into childcare is higher from part-time work than full-time work (by 4.7 percentage points) at the start of the sample period. The inflow into childcare remains higher from part-time work than full-time work as the women age, although the inflow rates from both states fall steadily. By the age of 33, 2 per cent of women in full-time work enter childcare over the year compared with 4.6 per cent of women entering child care from part-time work. In passing, we note that few women seem to move from part-time work to full-time work, and the transition rate falls as women age. At the start of the sample period, only 7.8 per cent of women in part-time work do so and just 3.3 per cent make this move by the end. Neither do many women move in the opposite direction (from full- to part-time work). This seems to be consistent with Blank's (1989) findings for the US that, for women of this age group, part-time work does not act as a stepping stone back to the world of full-time work.

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[4] These figures are very similar to those of Blank (1989) who uses a sample of all women of working age in the US.

[5] Aggregate female employment did not suffer unduly in the last recession.

In the previous Chapter, in Section 6.5, we took a long run view of the steady-state gender wage gap. We now use a similar long run equilibrium approach to gain insight into the expected proportion of women in each labour force state at each age level when the system converges to a steady state. In a steady state, the inflows to each of the four states (FT, PT, OTHER and CC) are equal to the outflows. So the matrix of transition probabilities, T, when multiplied by the proportions in each state equals the vector of steady state proportions, $Tx = x$. Rearranging this yields

$$(T-\lambda)x=0, \text{ for } \lambda=1 \qquad (7.1).$$

Given T, the vector of steady state proportions can be found as the eigenvector corresponding to the unit eigenvalue, λ, in (7.1). Using estimates of the inflow rates and the outflow rates for the four states to calculate T, for each year, we calculate the steady state proportions given in Table 7.3. Consistent with the transition rates in Table 7.2, as the NCDS women get older, the proportion located in the childcare state can be seen to be falling. When these women return to the labour market, they have a greater propensity to return to part-time work. The age-specific steady state full-time proportions are little changed over the sample period at around 34 per cent. For this cohort, child care and part-time work appear to be close substitutes. The steady state share of those in childcare falls from 45 per cent when the sample is aged 23 to 17 per cent when the sample is aged 33. The steady state share of those in part-time work rises from 17 to 41 per cent.[6]

This finding is currently unreported in other studies of the labour market behaviour of women following childbirth. The way we have developed our analysis here enables us to investigate the experiences of women at the age that they re-enter the labour market. In contrast, Joshi *et al* use information on gap length for the first birth to study full- and part-time participation at age 33. This is not what we do here. By virtue of the way we have organised the data, we are able to analyse transitions at the point of re-entry. Via the precise location of the month at which a female makes the transition back to work, we are able to identify marital, fertility and other characteristics at that point, and to follow subsequent behaviour. In what follows, we analyse why, as the age at which

[6] The sample proportions of full-time work, part-time work and child care in the respective years are: .66, .07, .20 in year 81/82, .47, .18, .28 in year 85/86, and .40, .19, .21 in 1990/91.

women return to work increases, the probability of returning to part-time employment is higher.

7.4 Subsequent Re-entry: Full- or Part-time?

The previous section showed that women who have children are more likely to return to work part-time, the older they become. Why might we expect that a woman nearing, or in, her thirties, who takes an extended period of childcare is less likely to return to the labour market on a full-time basis? Simple labour supply theory would suggest that the presence of a working partner, assuming that this is exogenous, would increase household income and reduce female labour supply. This could be manifested as an increased chance of returning on a part-time basis. The receipt of a partner's income may also spread the fixed costs of childcare, making the return to full-time work less necessary. The undertaking of part-time work also lends itself to the combination of work and domestic responsibilities for these women. As the female's partner ages and gains experience, we would expect that the income from his work to rise correspondingly. This may then be consistent with the pattern detailed above. The non-pecuniary benefits of time spent with children and hence of part-time work may propel mothers in their thirties into part-time work. In the case of single mothers, without access to income from another source, the fixed costs of childcare and the nature of the benefit system are such that either full-time work or non-work are the two viable options. Ermisch and Wright (1991 (b)) argue that younger children, and more children, make more demands on the mother's time and thereby increase the utility from not being in work. They also find that older single mothers are less likely to re-enter full-time work compared to never to returning to work. (However, they ignore the possibility of returning to part-time work.)

Certainly, the age of the mother and the age of children are positively correlated. Blank (1991) documents this, and the number of children, as "the major correlate of changes in labour market status for women." As the decision to have a child is delayed, it may be that the arrival of a first child is a more significant event and raises the utility from being at home. For the older mother, with a continuous work record before childbirth, the decision to have children is based upon the ability to both economically provide for

them, and to maintain a link, through either custom or habit, with economic activity. We would expect the probability to return to work upon a full-time basis to be lowered with the number of children, as the mother balances time spent in work and time spent at home.

The availability of childcare is also pivotal to the return to work but, when modelling, it is potentially endogenous. The type of childcare chosen may be heavily dependent upon whether a full- or part-time job is taken. Childcare type is therefore excluded from the subsequent regressions. Table 7.4 does, however, document the different types of childcare used by NCDS women as they age, across full- and part-time work status. Most women, whether full- or part-time use informal types of childcare. For the most part, this involves the use of grandparents or spouse. Women in part-time work tend to make more use of their spouse than grandparents, but the difference is not large. Formal childcare as represented by the employment of a parental assistant, is used more by full-time workers, although this never amounts to more than 16 per cent at any age. Rather than estimate a predicted childcare cost variable, as, for example, Blau and Robins (1991), we use the number and age of youngest child as a proxy for the potential childcare cost.

A spell out of work has less impact on re-entry wages in part-time jobs. This is because, as Chapter 5 shows, the returns to experience are lower in part-time work. Chapter 6 also shows that the full-time - part-time entry pay gap has risen since 1985. As the cohort of NCDS women ages, then the penalty for returning to work part-time (as reflected in the loss of experience) is less significant compared to the loss for full-time women. The faster that women return to work after childbirth, the nearer their actual labour market experience to their potential experience. Given the strong impact of experience in the determination of wages, the smaller the wage penalty for time out for women who minimise on hometime. The NCDS Sweep 5 has information on the current or last wage at point of interview, not at the point when the individual necessarily returns to work. In order to capture the opportunity cost of not working, we include an imputed wage. In this analysis, the wage offer is imputed from a regression of hourly re-entry wages on a set of human capital variables, as indicated by educational qualifications and the amount of work experience. We use entry wages rather than an

average wage variable as used in most studies, (see Joshi, Macran and Dex (1996), for example), due to the gap in entry wages and average wages documented in Chapter 6. This is because women who return to work after a break do not typically receive the average hourly wage. The mean hourly entry wage is estimated using the General Household Survey (GHS) data set described in Chapter 3. For each year covered by our NCDS sample, the GHS has information on earnings, personal characteristics and labour market status (one year earlier). Following Chapter 6 and Gregg and Wadsworth (1996), we define an entry job as one which was taken up at some point in the preceding year conditional upon not being in work one year ago. Due to issues of sample size, we estimate these entry wage equations conditional on age, by pooling consecutive years of data. Unlike the NCDS, the GHS has no information on actual work experience, so we use entry wage equations matched by age instead. For women aged 23 to 24, the entry wage is estimated on the years 1981-1982 and so on. We restrict our GHS sample to women only. The predicted earnings from these regressions are used to form the imputed likely wage offer for the female returners. The hourly wage is indexed to a base of January 1992. The regressions are reported in Table A 7.1.a.

We choose to use a single predicted wage rather than split the wage into two different wages pertaining to full- and part-time work, because of concerns of the potential endogeneity that splitting the wage would create. For the same reason, we choose to use hourly rather than weekly wages, since weekly wages are more obviously correlated with full and part-time working. The imputed wage is identified by the presence of industry variables in the wage equation.[7] Several studies (such as Krueger and Summers (1988)) have shown the importance of industry in the determination of wages. Compensating wage differentials, efficiency wages or union effects are usually invoked to explain these industry effects. However, the industry is not likely to affect the decision to return to work (other than through the wage rate). Thus, the industry variables do not appear in the set of explanatory variables in the return to work equations that follow.

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[7] Joshi, Macran and Dex (1996) use ability at age 11 to identify their imputed wage variable. Our use of industry does not imply that women look for work in only specific industries, merely that female wages differ across industry.

7.4.1 Estimation

The probability of participation in either full or part-time work by all women who have experienced a childcare break is modelled in this section as a probit. We restrict the sample to the 1690 subset of returners to work of which 1364 have completed a child care period and returned to part-time employment, and 326 have returned to full-time employment. Although the information on this rests on a female's perception of whether or not she was in full- or part-time work, the instructions of the interview encourages women who work less than 30 hours per week to classify themselves as part-time.[8] The dependent random variable, Y, is dichotomous, taking on the value 1 if the female has taken up a full-time post and 0 if a part-time job has been taken. So we have

$$P(Y = 1|X) = \Phi(\sum \beta_k X_k) \qquad (7.2)$$

where the parameters β_k are the parameters of interest and Φ is the standard normal cumulative distribution function. Using maximum likelihood estimation, we find the estimates of β_k that maximise the probit likelihood. In order to contrast the behaviour of women of different ages at return, we split our sample into mothers above and below the age of 28. This cut off is the point at which the gap between the relative chances of moving into part-time (rather than full-time) work are maximised whilst retaining a tractable sample size for estimation. Relatively small sample size prevents us from running separate estimates of the model at each age.

Table 7.5 gives the sample means of the explanatory variables used in the subsequent regressions for the three groups. All variables are calculated at the point of re-entry using the information contained in the NCDS life histories. This restricts the set of variables that can be used somewhat, as only certain variables can be traced through the NCDS over time. The sample mean probability of returning to full-time work drops from 23 per cent to 17 per cent across the two sub-groups. Women over the age of 28 tend to be more likely to have left a part-time job before their break and to have more children with the youngest child more likely to be over the age of 4 years.

The results from the estimation procedure are presented in Table 7.6. Since the coefficients from a probit regression are not immediately intuitive, we give the marginal effects for each variable along with their standard errors (adjusted for heteroscedasticity). So we have $dP/dx_i = \beta_i * \phi(\beta X)$ for a continuous variable x_i where the standard normal probability density function ϕ is evaluated at the sample mean. For dummy variables, the marginal value of a variable x_i is calculated by adding β_i to the sample mean, and calculating the new cumulative distribution function, Φ_i. In effect, we estimate the probability of being in full-time work, with and without, the particular characteristic holding all other variables constant.

7.4.2 Probit Results

The impact of the age of the female returner on the probability of returning to full-time work not controlling for any other factors is shown in Table 7.6 (column I). Women under the age of 28 are 5 percentage points more likely to return to full-time work. This should be viewed as the raw difference in difference between the relative entry rates above and below the age of 28. The average gap below the age of 28 is around 7 points whilst the average gap above this age is around 12 points (see Figure 7.1). Hence, the difference in difference of 5 percentage points. The subsequent columns introduce a set of controls for observable characteristics that seek to explain the difference between women below and over the age of 28. For the most part, the difference is accounted for by the additional explanatory variables. The coefficient on age becomes smaller and statistically insignificant.

From Table 7.6 column II, we observe that the age of the youngest child in the individual's family appears to have the largest impact on the probability of returning to full-time work. The younger the child, the less likely the mother is to return full-time. Across the whole sample, mothers with a youngest child under one year are some 9 percentage points less likely to return full-time. This is in line with previous work that suggests an increase in the probability of entry to full-time employment for mothers as the age of the youngest child increases (for instance, Ermisch and Wright (1991 (b))

[8] We prefer to use this self-reported part-time variable as there are fewer missing values for this in contrast to the responses to the questions asked on the usual hours worked.

using Women and Employment Survey). The total number of children in the household has a negative, but not significant impact on the probability of returning to full-time work lowering the probability by some 2.4 percentage points for each additional child. This is consistent with the findings of Joshi *et al* (1996). The greater the number of children, the greater the burden of obtaining and paying for quality childcare.

Another interesting feature of Table 7.6 is that being married at the point of re-entry to work (*married*) is positive and significant. Thus, for the group of all mothers as a whole, being married on return to the labour market is positively associated with returning full-time: raising the probability by almost 7 percentage points, other things equal. For all mothers, the duration of time spent in the provision of childcare appears mainly negative but not significant in the process of returning to full-time work (compared to the reference group of more than 3 years time out). The length of pre-break work experience appears to be small and generally insignificant. Having had a spell of work before taking a break appears to have no effect on the return to full-time work for mothers once the type of job held is controlled for. The possession of educational qualifications does not in general affect the outcome.

The effect of the imputed wage is negative and significant only at the 10 per cent level. A ten per cent increase in the wage offer, (increasing the log hourly wage by 0.1), reduces the probability of returning to full-time work by around 1.6 percentage points. As the potential wage rises, women substitute childcare hours for work hours, so we observe the reduced probability of returning full-time. This result is in contrast to that found in Joshi *et al* (1996). This may reflect differences in the construction of the imputed wage between the two studies. On average the predicted entry wage rises with age and age is negatively correlated with the return to full-time work in our data. The other variable used to capture household income effects is the occupational status of the partner at point of re-entry. This variable is never significant.

Whether a female worked part-time before exit to childcare appears to have a significantly positive impact on the likelihood of returning to part-time work. Having a history of part-time jobs makes it far more likely that a female will continue to work part-time.

Columns III and IV split the sample by age to highlight any differences in the effects of given characteristics between the two groups.[9] Whilst the sample split is not accepted, there are a few differences in the effects of individual coefficients that are noteworthy. The negative effect on returning to full-time work of the age of youngest child is more pronounced for younger workers, (and significantly different between the two groups for youngest aged 1-2 and youngest aged 2-3). How does that effect change with an increase in the age of the youngest child and the number of children? As children become of school age, their impact on female labour supply becomes less crucial. Most of the positive married effect is generated amongst the older returners. For the group of mothers who have delayed family formation until after the age of 28, being married at the point of re-entry to work is associated with a higher probability of returning to full-time work. One of the most difficult times of the day to organise formal childcare is early in the morning. For dual partner households, the burden of childcare at these times can be shared, making a return to full-time work easier. The negative effect of the expected wage is also more pronounced for the younger group. There is also some evidence that longer spells of time out result in differential exit states across the two age groups, though we return to this issue in Section 7.5.

To summarise these results, Table 7.7 presents predicted probabilities of returning to full-time and part-time work respectively, conditional on a set of characteristics, using the estimated coefficients from Table 7.6 to construct the predicted probabilities for each type.[10] The table confirms that the probability of returning to full-time work rises with the probability of being in full-time work previously and the age of the youngest child. However, there are significant differences in the estimated probabilities across the two age groups. The estimated probability of returning to full-time work for Group C is

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[9] The likelihood ratio test for the sample split across age groups is given by - 2 ln (a/b) where a is the restricted and b is the unrestricted likelihood. Taking the restricted likelihood from a probit on the whole sample excluding the age variable, we have -2 ((-737.7) - (305.9 + 411.8)) = 41.0 ~ χ^2 (34) This is not accepted at the 10% level of significance (44.8). Alternatively using the Akaike information criterion to discriminate between the non-nested models, AIC = - 2 (ln L) + 2 (k+1)
where k is the number of covariates, then again the sample split is not accepted.

[10] For example, the predicted probability of being in full-time work for a married woman aged 25 is given by

$$\Phi(b[cons] + b[Age\ 25] + b[married])$$

where Φ is the cumulative standard normal distribution function and b[.] are the estimated coefficients from Table 7.6.

more than twice as high for those aged 28 and over. In contrast, the estimated probability of returning to full-time work for those with children under the age of one, Group B, is nearly zero for those over the age of 28 compared with around 4 per cent for those under the age of 28.

So what would appear to explain the difference in the transition rates of mothers who return to full- and part-time work across age groups? The results above suggest that differences in characteristics rather than the different effects of given characteristics tend to explain the observation. Women who are older on return are more likely to return to part-time work because they have more children and their potential earnings are higher. This allows them to combine the roles of carer and part-time worker.

7.5 Analysis of Childcare Duration

7.5.1 Introduction

The section above catalogued the experience of moving from childcare to full- or part-time work for a group of British women. The issue centred on the dynamics of these transitions, given information on individual and household characteristics. More women leave childcare for part-time work than leave for full-time work at each age. Thus, the duration of a spell in childcare will be longer if the ultimate destination is full-time work. This section contributes to our understanding of the dynamic process by analysing the duration of time spent in childcare before exit to other states in more detail. We again concentrate on the exit states of full- and part-time work.

Before looking at the return to work conditional on duration in more detail, we outline the NCDS evidence on the distribution structure of the principal labour market states for the full sample of women. Using the NCDS work history data, we can calculate the duration in months of any spell and sum the spells for each individual woman. Table 7.8 illustrates the frequency distribution for each state. We count the number of times each individual occupies each state. Most women only experience one spell in any state.[11] Of those women who ever have a part-time job, for approximately two-thirds that one spell is their only experience of part-time work throughout the sample period.

[11] This could, of course, include contiguous moves (that is, job to job, for example) in the same state.

However, part-time work is the most transient of all the states observed. Roughly three quarters of the sample of women experience one spell of childcare, unemployment or full-time work.[12] Education and training are usually only ever experienced once.

Table 7.9 presents the mean completed duration and the associated standard deviation in the main states, whilst Figures 7.2 to 7.5 graph the completed spell distributions. The average mother by the age of 33 will have spent nearly 2 and a half years out of work in childcare: more than her individual experience of full-time and part-time work. The mean duration of unemployment spells in Figure 7.4 is 9.5 months, whilst the median length is 6 months, indicating the presence of a small number of long-term unemployment spells in the sample. The central 50 per cent of unemployed workers experience spells ranging from 3 months to 11 months. The distribution of the completed duration of spells in childcare is spread up to and just over 8 years in length. The mean duration of childcare spells is 29 months whilst the median length is 22 months (Figure 7.5). The distribution of child care is less skewed and the inter-quartile range is much broader, from 10 months to 43 months. Figure 7.3 shows how part-time spells of work are clustered around the range 1 to 2 years duration. Figure 7.2 shows that, excepting the peaks in the data at spells of 6, 12 and 18 months (which may be due to rounding by individual respondents), the distribution of full-time work spells is less rightward skewed than that of part-time work. The mean duration of full-time spells is 25.8 months whilst the median length is 19 months. (In contrast, the mean duration of part-time spells is 19 months whilst the median length is 13 months.) The inter-quartile range contains the central 50 per cent of employees and, in the case of full-time work, the central 50 per cent exhibit spell lengths between 8 and 36 months. The spells of full-time work are spread more evenly in terms of spell length than those of part-time work, with some women in our sample experiencing nearly as much as 10 years of full-time employment. The inter-quartile range for part-time spells ranges from 6 to 25 months.

Table 7.10 compares the completed duration of the childcare state with the age at which the female returns to the labour market for the group of childcare women as a whole (All), for women who return to full-time work, (FT), and for women who return to part-

[12] Women who do enter childcare have more than one childcare spell, typically two.

time work, (PT). There is a clear trend for completed outspells to become longer as the age at return rises. This holds for returns to both full-time and part-time jobs, with little difference in the average out duration at any age between the two states, apart from the final two years of the cohort. Whilst the average duration of the childcare spell may be similar for entrants into full-time and part-time work, it may be that the determinants of that spell length differ. It is to this issue that we now turn.

7.5.2 Competing Risks Models of Duration

A key characteristic of the data under study in the Section 7.3 is the multiple exit states for each NCDS female who takes a break in employment for childrearing purposes. The group of models which encompass such multiple exits have received much recent attention in the competing risks literature.

Most of the economic research dealing with hazard functions assumes a single process that produces the termination of a spell. Ermisch and Wright (1991 (b)), for example, analyse periods of childcare which end with the commencement of a full-time job, ignoring exits to other states. However, in most situations, it is incorrect to assume that there is only one way of terminating a spell. A woman may adopt any one of a number of labour force states upon the termination of a childcare spell, and so a competing risks framework is more appropriate. In this section, we give a brief introduction to competing risks models, (see Lancaster (1990), or Pudney (1992), for more details).

Suppose there are M possible labour market states to enter on termination of a childcare spell. Envisage up to M independent random variables, $T_1,...,T_M$. These may be thought of as the latent durations to enter each destination state. T_m is the waiting time that elapses before the episode ends via risk m: in the absence of all other risks that might cause the interval to end. Which destination state is actually selected depends on which of the T_m is the smallest. It is this duration which we observe in our data set.

T_M has a hazard function $h(t, x ; \theta)$, at some duration, t. This indicates the probability of an interval ending conditional on the interval not being ended prior to t. That is, the hazard function represents the probability at which a spell will be completed during time $t+\Delta t$ (where Δt is some small interval) given that it has lasted until time t. Here, x is a

vector of values taken by a set of potential explanatory variables and θ is the vector of parameters requiring estimation. The hazard function may be defined in our notation as,

$$h(t) = \lim_{\Delta t \to 0} \frac{\Pr(t \leq T_m < t + \Delta t \mid T_m \geq t)}{\Delta t} \qquad (7.3)$$

The distribution for t can be characterised by a probability density function, pdf $(t) = g(t \mid x; \theta)$, and a conditional distribution function of the form, $Pr\ (t < T) = G\ (T \mid x; \theta)$. For given x, the conditional distribution function represents the proportion of observed durations that are expected to be less than some duration T. Its complement, $1 - G\ (T|x; \theta)$, represents the expected proportion of durations greater than T (the so-called survivor function.) Given a particular hazard function, it is possible to derive $g(.)$ and $G(.)$ and the survivor function, $S(.)$. It is assumed that the hazard function has a special form that makes modelling tractable, such as the following Proportional Hazards (Cox) specification:

$$h(t, x; \theta) = h_1 (x; \gamma) h_2 (t; \alpha) \qquad \text{where } \theta = (\gamma, \alpha). \qquad (7.4)$$

This representation lends itself to a variety of functional forms, but always implies that the explanatory variables influence the scale of the hazard rate, but not the nature of its dependence on time. That is, in the Proportional Hazards (Cox) model, the baseline hazard is multiplied in proportion to the associated characteristics, but it remains independent of the duration of the spell. The function, $h_2(t; \alpha)$, is the baseline hazard function and, in one of its most simplest forms, the baseline hazard may be normalised to unity.

Assuming $h_2\ (t; \alpha) = 1$, and h_1 follows an exponential distribution, the Proportional Hazard representation yields the following hazard

$$h(t, x; \theta) = \exp (\gamma_0 + x' \gamma) \qquad (7.5)$$

One reason for the popularity of the Proportional Hazard assumption is the tractability of the semi-parametric approach. It is possible to estimate the parameters of $h_1(x; \gamma)$ without the specification of a parametric form for the baseline hazard function, (that is, $h_2(t; \alpha)$). Moreover, Kiefer (1988) shows that in this case

$$d \text{ Ln } h(t, x; \theta)/dx = d(\gamma_0 + x'\gamma)/dx = \gamma$$

so the coefficient can be the (constant) proportional effect of x on the conditional probability of completing a spell. The common specifications for the Proportional Hazard functions are used for analytical convenience, as they lead to simple closed-form expressions for the probability density and conditional distribution functions.

Parametric assumption of proportional hazard models simply requires an explicit parameterisation of the baseline hazard function. One possible disadvantage of relying solely on an exponential distribution above is that this is indicative of so called memoryless models. That is, the hazard rate does not vary over time. It is possible to relax this assumption according to the following (Weibull) specification where now $h(t, x; \theta) = p\, t^{p-1} \exp(\gamma_0 + x'\gamma)$.

Notice that the Weibull specification exhibits positive duration dependence for $p > 1$, that is, the derivative of the hazard function with respect to time is positive ($dh/dt > 0$). It exhibits negative duration dependence for $p < 1$, and no duration dependence for $p = 1$. This group of parametric models are simple, but they do impose a structure on the data, so as a counter to this we initially also estimate the Proportional Hazards (Cox) model described above.

Extending the above notation, suppose there are m distinct processes which might lead to the ending of the spell of childcare and that each of these separate processes may be represented by a hazard function, $h_i(t, x_i; \theta_i)$, $i = 1,2,...,M$. Each destination state represents a different outcome, such as full- or part-time employment, or one of the other possible exits. Only a small number of women exit to these other states (precisely

79 women) and these we remove.[13] Following Narendranathan and Stewart (1993), and Dolton and O'Neill (1996), we assume that the competing risks framework maintains independence of the underlying stochastic processes describing time to exit to full- or part-time work. In the case of independent risks, we need to specify only the marginal distribution of each T_m. Also, in what follows, we do not consider any time-varying covariates. We consider here only the case that durations of childcare for each female are independent across spells. This enables us to specify a tractable model of the stochastic process which governs the labour market histories. The last independence assumption implies that any unobservable heterogeneity terms are not correlated across spells.[14]

We thereby develop a competing risks duration model of the probability of exit to full- or part-time work conditional on entry into a preceding state of childcare. The contribution of the i^{th} individual with an observed duration d_i and exit state K to the log likelihood is

$$\ln L_i = \ln h_{Ki}(d_i) + \sum_{t=0}^{d_i-1}\sum_{j=1}^{J}\left[\ln(1-h_{ji}(t))\right] \qquad (7.6)$$

$$= \ln h_{Ki}(d_i) + \sum_{t=0}^{d_i-1}\ln(1-h_{Ki}(t) + \sum_{j\neq K}\sum_{t=0}^{d_i-1}\ln(1-h_{ji}(t)) \qquad (7.7)$$

The log-likelihood may be partitioned into a sum of terms, each of which is a function of the individual cause-specific hazard. The parameters of a given transition may be estimated by maximising the likelihood separately with respect to each subset of parameters, treating durations which finish in other state as censored. For example, conditioning on entry into childcare, the probability of exit to either full- or part-time work is parameterised and estimated. Under the assumption of independence of hazards, the competing risks model yields separate estimates of hazard rates for each exit state. Essentially, the competing risks model conceptualises T_m as the time to outcome m if the transition to another outcome is not possible. The two resulting sub-

[13] All estimation was carried out with and without these 79 cases. Results were not altered by retaining these women and treating them as censored.
[14] This might be a limitation but it is left to future work.

samples of data are E_1, the set of returners to full-time work, and E_2, the set of returners to part-time work.

Following Narendranathan and Stewart (1993), we do not attempt to model unobserved heterogeneity. The authors report that existing techniques to deal with this problem produce estimates that are sensitive to the number of competing risks specified and the form of the hazard function. For these reasons, allowance for omitted heterogeneity is left to future work. As Gianelli (1996), we recognise that any left censored spells present complications when assessing the issue of duration dependence. We therefore restrict our sample to those observations for which we observe entry into the childcare state.

Our NCDS sample consists of a set of women who enter the childcare state at any time in our ten year window, rescaled to calendar time $t = 0$ and exits into work, either a full- or part-time, at some subsequent time. The precise time of entry to full- or part-time work is measured in months. Therefore, our observations consist of the duration of the spell, T, a variable j which indicates the destination of the woman at the end of the spell, and of a vector of explanatory variables, x.

7.5.3 Kaplan-Meier Estimates

As an introduction to this section, the non-parametric Kaplan-Meier product limit estimators (Kaplan and Meier (1958)) are used to summarise the duration data set. Let d_j be the number of individuals with completed spells in the sample with duration t_j for $j = (1,2,\ldots, K)$. In the competing risks model, exits to other states are treated as censored. So n_j are the number of spells neither yet completed or still to be censored after duration t_j such that

$$n_j = \sum_{i \geq j}^{K} (m_i + d_i) \qquad (7.8)$$

where m_i represent the number of censored observations between t_i and t_{i+1} . As before, the hazard represents the probability of completing a spell at duration $t_{j+\Delta t}$, conditional on the spell reaching duration t_j . The hazard function may be estimated by

$$h(t_j) = \frac{d_j}{n_j} \qquad (7.9)$$

This is essentially the number of failures (here, the number of exits from childcare) at duration t_j , divided by the number at risk at duration t_j. The Kaplan-Meier survivor function is then given by,

$$S(t_j) = \prod_{i=1}^{J} (n_i - d_i)/n_i = \prod_{j=1}^{J} (1 - h(t_j)) \qquad (7.10)$$

In what follows, we use only those observations with completed spells. Due to the nature of the data set, the only censored observations in our sample have to occur at age thirty-three. As we are investigating the impact of age on the process of returning to work, including age variables and allowing for censoring generates collinearity problems.[15] We therefore drop all returners aged thirty-three and leave the consideration of these women to future work. This gives a final sample of 1406 women with information on both the dependent and explanatory variables. The only censored observations remaining are those exits to either part- or full-time work in the competing risks framework.

It may be that even discarding those women returners aged thirty-three that the age variable is still highly correlated with the dependant variable. Due to the nature of the data set (namely, that the cut-off occurs at age thirty-three), women who start a spell of child care in their early thirties are more likely to have had a shorter completed spell than women who began a spell in their early twenties. However, the inclusion of an age variable may be justified on the grounds that it may capture the impact of a life-cycle intensity of participation effect. That is, the decision to return part-time, according to the human capital model, may rise with age, if workers have less time left to recoup the returns from investing in human capital investment. In this case full-time work may be less preferable to part-time work.

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[15] Some 868 women are censored in this way. (Some 36 % of the total number of women.)

For these reasons, we include an age variable in what follows, but we use the age at which the childcare spell finishes in preference to the age at which it started. The former age variable is less correlated with the duration of childcare spell than the latter. In our data set, spells that finish when women returners are in their thirties are more likely to contain a mixture of short and long spells, than those which begin when women are in their early thirties.[16] We also present estimates from which the age variable has been removed.

Tables 7.11 to 7.12 report the Kaplan-Meier estimates of the hazard rate and the survivor function for our sample for the group of women as a whole, for women who return full-time and for those who return part-time, respectively. Figure 7.6 graphs the hazard rate for two destination states (FT and PT). The first table makes no distinction whether the exit is into full- or part-time work, whilst the other two tables treat exits in to part-time and full-time work respectively as additional censored observations. The hazard functions for both types of destination states are very similar. In the case of all female returners to work, Table 7.11 gives the hazard rate estimates, which are broadly flat, remaining roughly at the same level, between 2 and 4 per cent, for all durations under 72 months. It rises thereafter when there exist relatively fewer spells to be completed. Approximately 14 per cent of the total stock of female returners leave childcare within the first six months. Some 11 per cent of the total stock of returners to part-time work leave childcare within the first six months. Table 7.12, gives the Kaplan-Meier estimates by destination, where exits into the other state (full-time or part-time work) are treated as censored. The Kaplan-Meier hazard function for exits to full-time work rises more steeply in the period between month 61 and month 100. Prior to this, the average monthly hazard into full-time work is around 1 per cent and the hazard into part-time work is around 3 per cent. Consistent with the findings in Section 7.3, the hazard rates into full-time work are always around half the size of those to part-time work at every duration. The standard errors on the two survivor functions indicate that the two processes are significantly different from each other.[17]

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[16] Witness the correlation coefficient between the length of childcare spell and the age at end (0.34) and the correlation between the length and the age at start (-.50). That is, the negative sign confirms that spells that start when women in the data set are older are more likely to be shorter.

[17] The two survivor functions are greater than two standard deviations apart throughout.

7.5.4 Competing Risk Model Estimation

In this section, we consider how the woman returner chooses to exit from childcare or domesticity into either part-time or full-time work depending on various family characteristics, the level of local labour market activity and her own human capital characteristics. Is there evidence that the number of children and the age of the youngest child have a positive impact on the duration of the childcare state, as well as on the probability of exiting to a particular work state? Is it more or less likely that a worker will exit to a full- or part-time job, the longer the time spent in the childcare state?

Table 7.13 presents maximum likelihood estimates of the Proportional Hazard (Cox) model of the duration of the childcare state for all mothers who have returned to work in our sample period of 1981-1991. Results are presented in terms of the impact of a unit change of each characteristic on the log of the relative baseline hazard of exit from childcare (effectively, $e^{x'\gamma}$ in Equation 7.5).[18] This representation makes it easier to compare the results across the Cox and Weibull models. A coefficient greater than unity would increase the probability of leaving childcare and therefore reduce the spell duration. Conversely, a coefficient less than one would decrease the probability of leaving. The smaller the coefficient the longer the spell. Column I gives the results from combining all exit states. Columns II and III allow the parameters to vary across exit states according to the competing risks framework.[19]

From Column I, we observe that the age of the youngest child of less than 1 year raises the hazard rate of ending a period of homecare relative to the reference category, (youngest aged 1-2 years), by around 43 per cent for the group of women returners as a whole. Thereafter, the older the youngest child becomes, the lower the relative hazard and the longer the duration spent at home. This may be picking up differences in labour

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[18] The standard errors relate to the log of these relative hazard coefficients.

[19] Following Narendranathan and Stewart (1991), we calculate the LR test statistic that the cause-specific hazards are proportional to one another (that is to say all coefficients except the intercepts are equal) as $LR = 2\ \{\text{Ln Unrestricted} - (\text{Ln Restricted} + Q)\}$ where $Q = \Sigma_j N_j \text{Ln}(N_j/\Sigma_k N_k)$ j, k = full, part-time and the N_j are the sample number of exits to each state. This gives
$2\ ((-7043.4 - 1348.0) - (-8441.5 + 224*\ln[224/1406] + 1182*\ln[1182/1406])) = 1333.4 \sim \chi^2(41)$,
so that the split into full and part-time exit states is easily accepted.

market attachment within our sample of women. Some women return quickly after child birth, others do not. The number of children also prolongs the period of time out. Women with four children have time out some 75 per cent longer than the default category of women with one child. Being in a part-time job before the time out spell began reduces the time out spell by around 170 per cent relative to those previously in a full-time job. This may reflect the female's need to resume earning. However, the presence of a working partner also raises exit times, and this effect is more pronounced the higher up the occupational scale the partner is. This is not consistent with a household income effect and it may be capturing the rise in multiple earner households observed by Gregg and Wadsworth (1996) and Davies, Joshi and Peronaci (1998). The other variable that affects duration significantly is age at exit. The older the female, the longer the period of time out. This effect may be because we are observing completed spells only, so that there is more chance of observing long spells as the cohort ages. It is notable that the effect of age is flat after the age of 26, so that this cannot account for all of what we observe. Mothers of young ages take shorter periods of time out for reasons that may have to do with the need to augment the existing stock of human capital and income. The removal of the age dummies (Table 7.13 (b)) makes little difference to the estimated impact of most variables. The exception is that the local unemployment rate dummies now become more significant and have a larger impact. The lower the unemployment rate, the longer the spell of childcare. The recession of the early 1980's was associated with high local unemployment rates that occurred when the returners were in their early twenties. This negative correlation between age and unemployment explains the increased significance of the latter when the age variable is removed.[20]

Columns II and III of Table 7.13 contain the competing risks estimation which enable us to separate out the contribution of any variable into the effects relevant to part- and full-time returners. We observe that the negative effect on duration of having a young child is fuelled by the behaviour of those who leave for part-time work. The youngest child age profiles are much steeper and more significant for this group. Likewise the positive effect on duration of more children is stronger for those who return to part-time work. Similarly, having had a job before exit to childcare which was part-time in nature triples the hazard rate of exit from childcare to part-time work, whilst the impact on duration of

[20] The correlation coefficient between the unemployment rate and age at the end of spell is -.68.

having had a part-time job for full-timers is only 50 per cent relative to those previously in full-time work.

In contrast, being married raises the hazard rate of full-time workers exiting from childcare by around 60 per cent, whilst there appears to be no impact on the hazard rate of part-time workers. Given the paucity of public provision of childcare, this result provides further evidence of the benefit of being in a relationship with a spouse or partner in the process of returning to work full-time. The rise in duration of time out with age is also more pronounced for those who return to full-time work, though again the profile is reasonably flat after the age of 26 for both groups. Local economic conditions, as measured by the regional unemployment rate, are also stronger for those who return to full-time work. Those in low unemployment regions tend to have longer durations before returning to full-time work. This result may suggest those in low unemployment regions can afford to be more selective over when to return to work. The effect is not significant however for the majority who enter part-time work.

Table 7.14 reports Weibull estimates of the same events. The results are practically identical in size and significance to the Proportional Hazards model above. The Weibull specification confirms the existence of positive duration dependence in the sample, which is stronger for those who leave for part-time work.

In order to summarise the impact of these estimated parameters on the length of time out, Table 7.15 reports the predicted values of time out, in months, using a basket of characteristics and a transformation of the Weibull parameter estimates from Table 7.14. Kiefer (1988) shows that it is possible to recast the parameter estimates into a form which makes the log of duration a linear function of each variable,[21]

$-Ln\ H_0 = x'\gamma + \varepsilon$, where H_0 is the integrated baseline hazard rate. For the Weibull case, $H_0 = \int h_0\, dt = \int p\, t^{p-1}\, dt = t^p$, so that $-p\ Ln\ t = = x'\gamma + \varepsilon$, and the effect of a unit change in a variable on the log of duration is given by $dLnt/dx = -\gamma/p$. This specification also belongs to the class of accelerated failure time models, since the duration of time

[21] Kiefer (1988) shows that the random variable $\varepsilon = -Ln\ H_0 - x'\gamma$ has an extreme value distribution, where H_0 is the integrated baseline hazard function. Hence any proportional hazard model can be written in the form $-Ln\ H_0 = x'\gamma + \varepsilon$.

out is then accelerated or decelerated according to whether the set of variables increase or reduce exit times relative to the baseline hazard, (the constant term in the linear specification). Since Table 7.14 reports coefficients, *b*, in relative hazard form rather than the γ, the appropriate transformation is $-exp(b)/p$.

The estimated mean durations in Panel B of Table 7.15 indicate that, relative to the sample means, the models tend to underpredict the duration of return to part-time work and over predict the length of return to full-time work. For given characteristics, those returning to full-time work are always predicted to have a longer period of time out of work than those returning to part-time work. The estimated durations also reflect the dominating impact of age and age of youngest child on the return to work.

7.6 Conclusion

Several features stand out here from our earlier Chapters. Not only do women who take time out to look after children experience significantly lower earnings than those who do not but the longer the length of time out, the longer the earnings penalty. This penalty is magnified if the woman returns to part-time, rather than full-time, work. This Chapter set out to identify the principle features of the duration of time out and the nature of the subsequent re-entry. We have shown that the relative propensity to return to part-time work rises with age of the mother. For our sample of women who return to work before the age of 33, women who experience childcare breaks that end relatively early in their careers spend less time out of work and are more likely to re-enter to full-time work. The age and number of children appear to be the most important factors behind this observation. Women are more likely to return to full-time work, the fewer the number of children they have and the older the children are. There appears to be less difference in the length of time out according to education, region, local economic conditions, or predicted income for this group of women. There also seems to be little evidence that women in the age range covered by the NCDS cohort use part-time work as a stepping stone to full-time work. If policy makers are concerned about these effects then it may be that greater provision of child care facilities may make the return to work easier for those women more marginally attached to the workforce, thereby reducing the length of time out and hence earnings loss. However this alone may be insufficient to encourage

women back into full-time rather than part-time work. Despite the fact that part-time work is relatively low paid, the majority of women continue to use this type of work in order to combine the worlds of home and work. As this is the outcome of the inter-relationship of the various socio-economic forces at work, perhaps one way forward would be to improve conditions in part-time work.

Figure 7.1 Outflow Rates from Childcare by Age

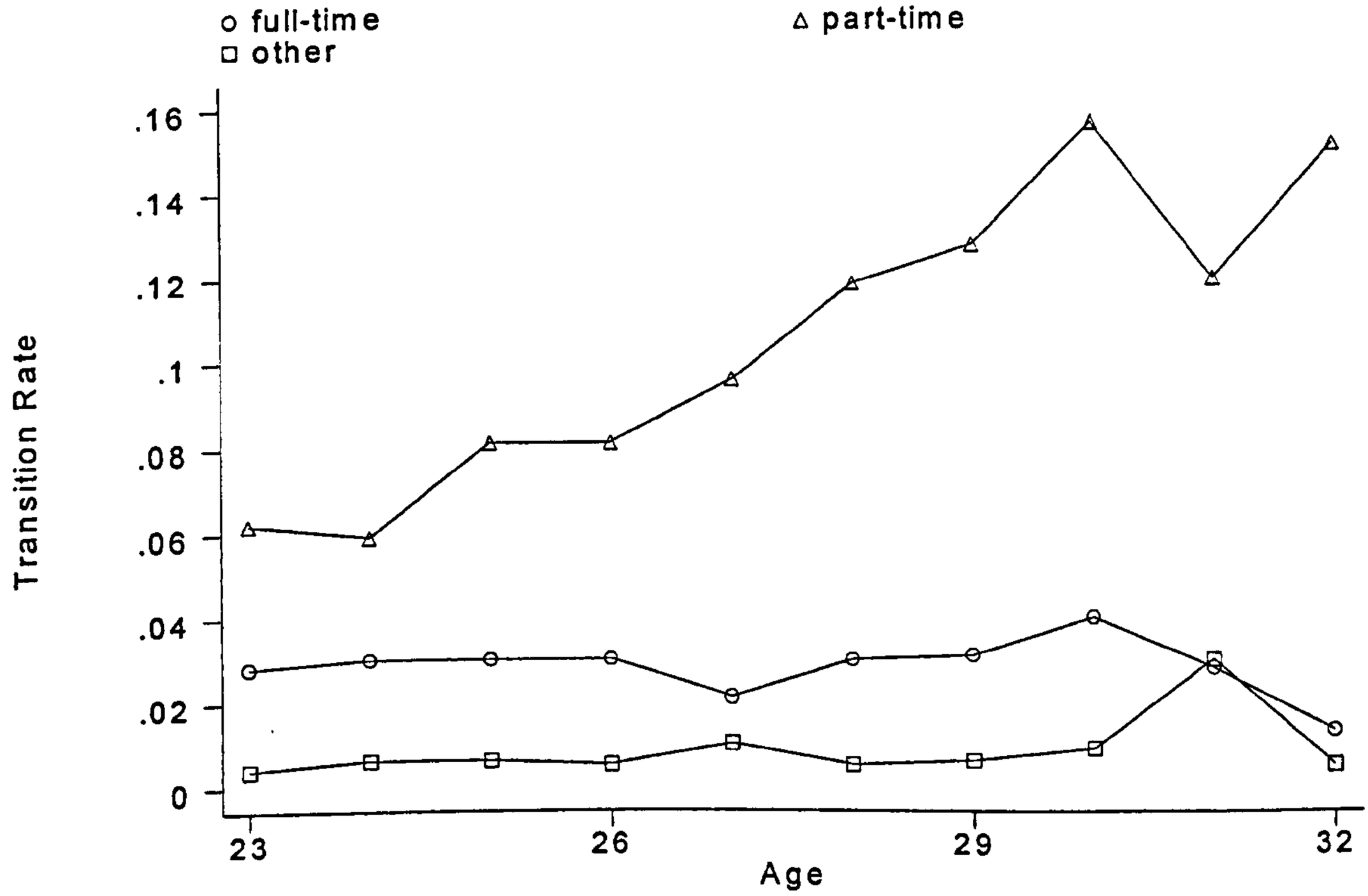

Figure 7.2 Distribution of Completed Spells in Full-time Work

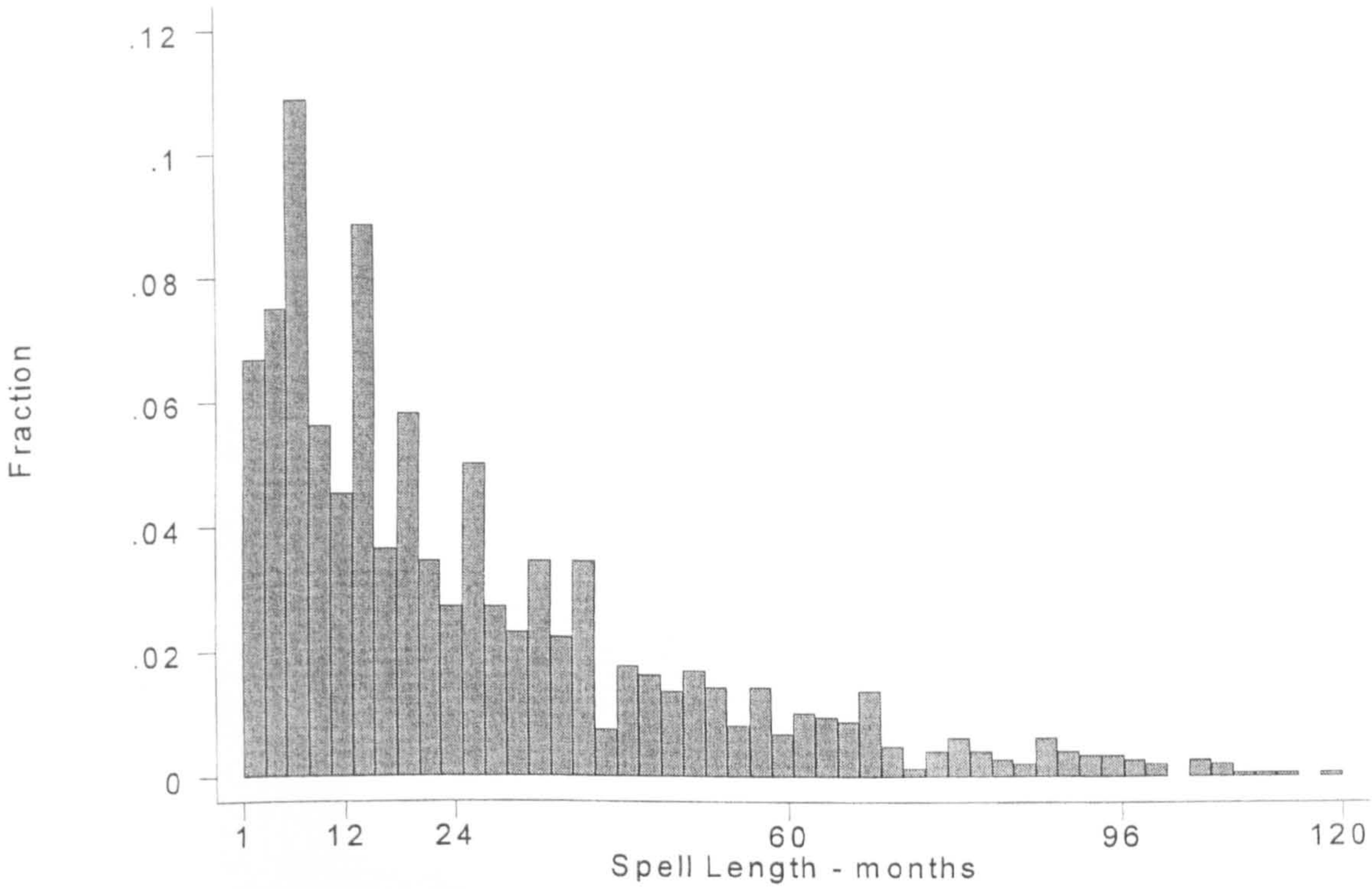

Figure 7.3 Distribution of Completed Spells in Part-time Work

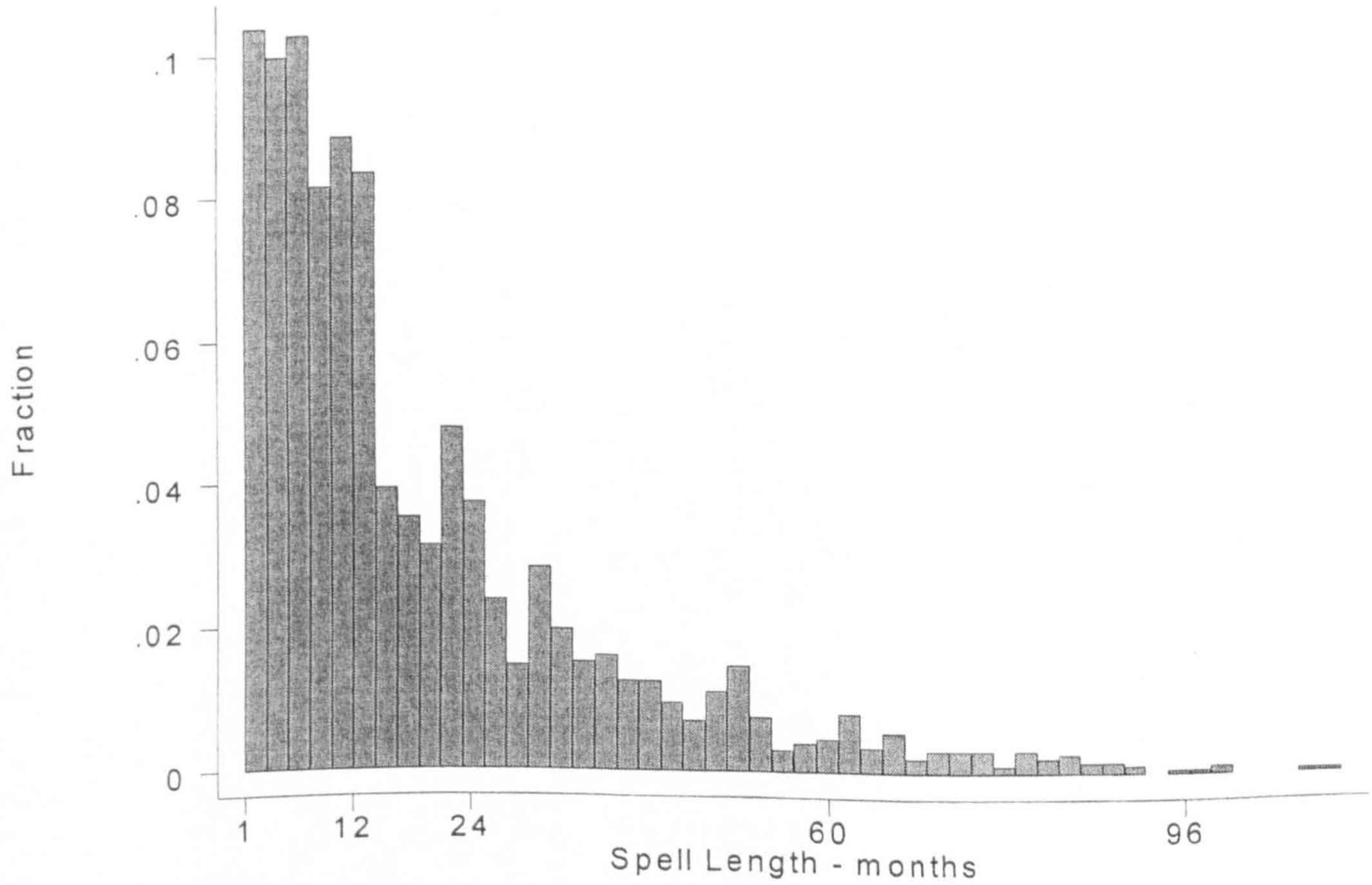

Figure 7.4 Distribution of Completed Spells in Unemployment

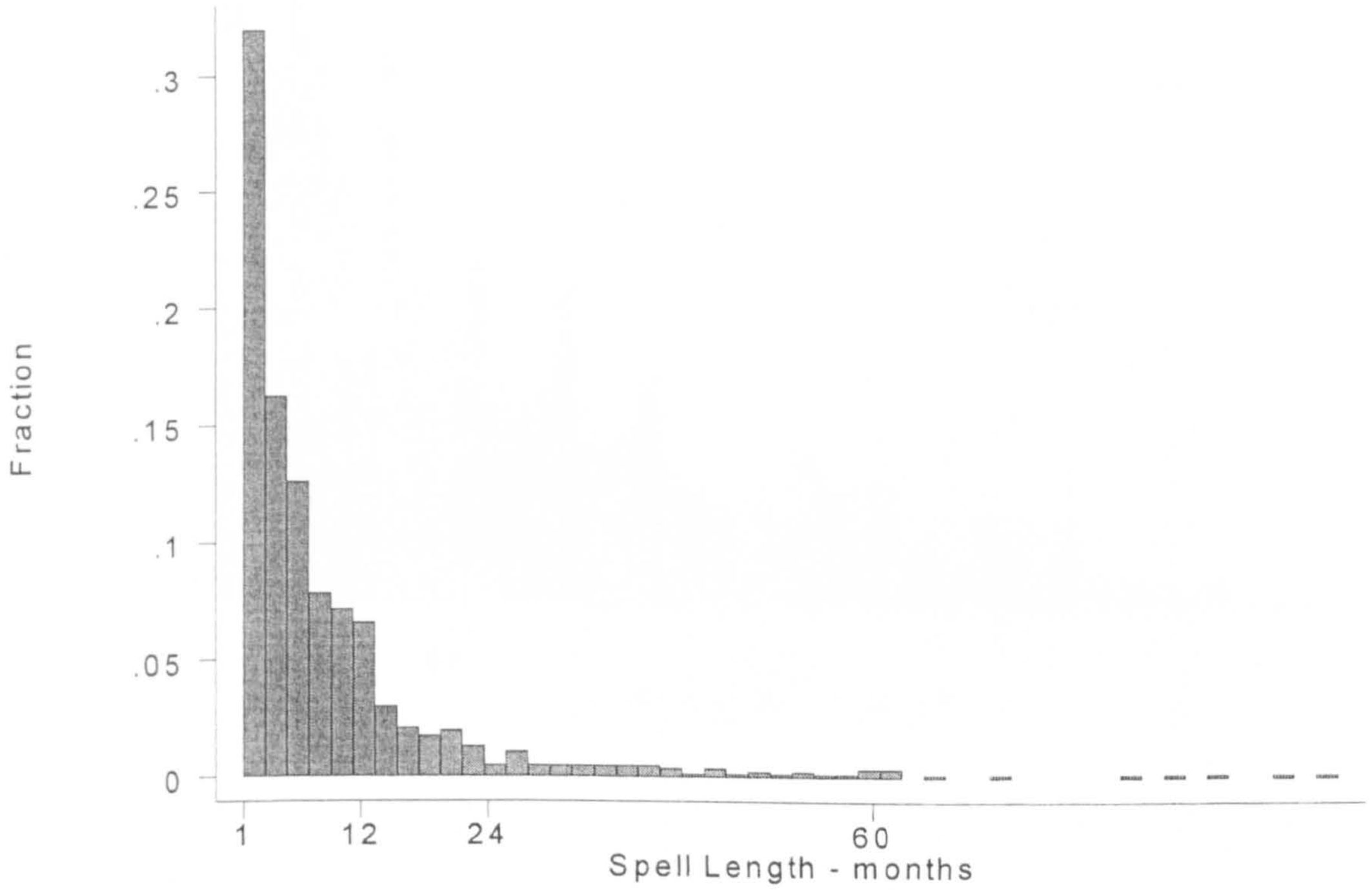

Figure 7.5 Distribution of Completed Spells in Childcare

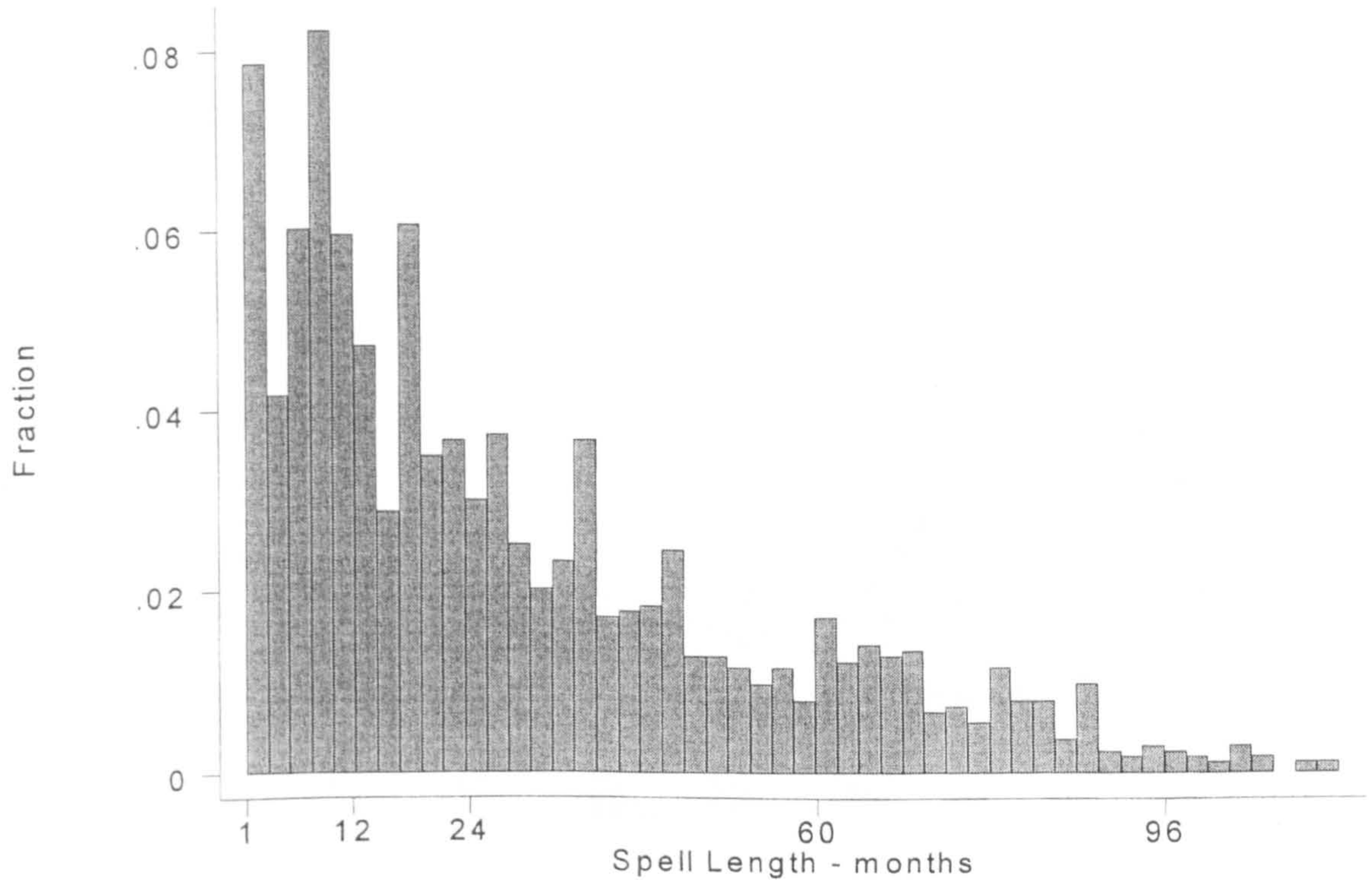

Figure 7.6 Hazard Rates out of Childcare

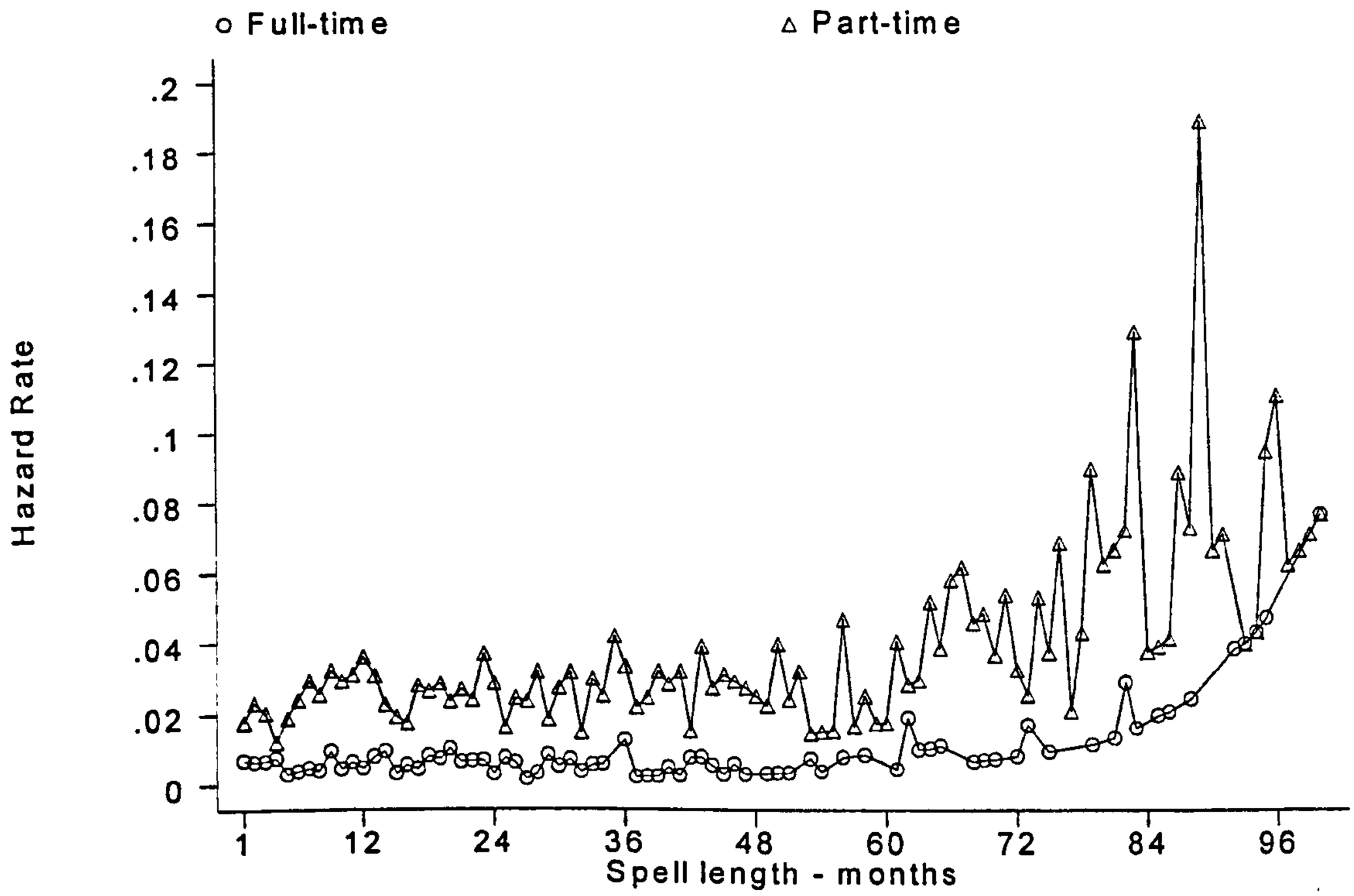

Table 7.1 Annual Transition Rates from childcare among adult women, 1982 –91

Destination Year (Age)	*CC-FT*	*CC-PT*	*CC-OTHER*	*Total Outflow Rate*
1982 (24)	.028	.062	.004	.094
1983 (25)	.030	.059	.006	.095
1984 (26)	.030	.081	.006	.117
1985 (27)	.030	.081	.005	.116
1986 (28)	.021	.096	.010	.127
1987 (29)	.030	.119	.005	.154
1988 (30)	.031	.128	.006	.165
1989 (31)	.040	.157	.009	.206
1990 (32)	.028	.120	.030	.178
1991 (33)	.013	.152	.005	.170
Average	.028	.111	.007	.146

Sample: All female returners

Table 7.2 Labour Market Transition Matrices by Age

Age 23 - 24

1982 / *1981*	*Full-Time*	*Part-time*	*Child Care*	*Other*
Full-Time	.902	.014	.063	.021
Part-Time	.068	.800	.110	.022
Child Care	.028	.062	.906	.004
Other	.277	.042	.049	.632

Age 27 - 28

1986 / *1985*	*Full-Time*	*Part-time*	*Child Care*	*Other*
Full-Time	.902	.021	.057	.020
Part-Time	.043	.849	.083	.025
Child Care	.030	.119	.841	.01
Other	.141	.081	.048	.73

Age 32 - 33

1991 / *1990*	*Full-Time*	*Part-time*	*Child Care*	*Other*
Full-Time	.935	.024	.022	.019
Part-Time	.033	.901	.046	.02
Child Care	.013	.152	.830	.005
Other	.101	.101	.032	.766

Annual Average

Destination state / *Origin state*	*Full-Time*	*Part-time*	*Child Care*	*Other*
Full-Time	.912	.019	.049	.020
Part-Time	.047	.856	.074	.023
Child Care	.028	.111	.854	.007
Other	.167	.083	.042	.708

Table 7.3 Estimated Steady State Proportions

Using data from:	*Age*	*Full-time*	*Part-time*	*Childcare*	*Other*
1981-82	23	0.345	0.171	0.449	0.035
1985-86	27	0.322	0.296	0.279	0.102
1990-91	32	0.349	0.414	0.170	0.067

Table 7.4 Proportion of Female Returners using Childcare Types by Age at Return to Work

		% using Childcare Type					
Age	Job type	Grand parents	Spouse	Friends	Nanny	School	Other
23	PT	24.5	39.7	4.6	4.3	18.5	8.4
	FT	25.6	33.7	6.9	9.4	15.0	9.4
24	PT	17.4	39.1	6.5	0.0	19.6	17.4
	FT	14.3	42.9	7.1	7.1	14.3	17.4
25	PT	39.1	30.4	8.7	0.0	13.0	8.7
	FT	20.0	40.0	5.0	0.0	25.0	10.0
26	PT	26.3	34.2	6.6	4.0	19.7	9.2
	FT	19.2	26.9	7.7	11.5	23.1	11.5
27	PT	27.1	43.0	6.5	2.8	11.2	9.4
	FT	31.6	31.6	5.3	5.3	10.5	15.8
28	PT	31.8	37.1	3.8	3.8	16.7	6.8
	FT	16.1	35.5	9.7	16.1	12.9	9.7
29	PT	25.5	43.3	2.8	5.0	19.9	3.6
	FT	25.0	21.4	10.7	10.7	25.0	7.1
30	PT	24.2	37.9	5.0	3.7	19.9	9.3
	FT	23.1	30.8	5.1	7.7	20.5	12.8
31	PT	19.8	46.0	2.7	5.4	18.0	8.1
	FT	26.7	50.0	3.3	10.0	3.3	6.7
32	PT	24.5	35.0	4.2	4.9	22.4	9.1
	FT	36.0	36.0	8.0	12.0	8.0	0.0
33	PT	16.8	43.7	4.2	6.6	19.8	9.0
	FT	57.1	21.4	7.1	7.1	0.0	7.1
Total	**PT**	**24.5**	**39.7**	**4.6**	**4.3**	**18.5**	**8.4**
	FT	**25.6**	**33.7**	**6.9**	**9.4**	**15.1**	**9.4**

Sample: All female returners

Table 7.5 Sample Means of Variables in Probit of Return to Full-Time Work:

Variable	Total		Age<=28		Age>28	
	Mean	St dev	Mean	St dev	Mean	St dev
Share return Full-Time	.19	.40	.23	.42	.17	.37
Age < 28	.39	.49				
Childcare <12 months	.19	.39	.16	.36	.21	.41
Childcare 12-18 mths	.17	.37	.14	.35	.18	.39
Childcare 18-24 mths	.11	.32	.08	.27	.14	.34
Childcare 24-30 mths	.20	.29	.07	.25	.11	.32
Childcare 30-36 mths	.07	.26	.05	.23	.08	.28
No. of Children	1.87	.81	1.64	.75	2.02	.81
Youngest child <1	.05	.22	.07	.25	.04	.19
Youngest child 1-2	.21	.40	.27	.44	.17	.37
Youngest child 2-3	.20	.40	.23	.42	.17	.38
Youngest child 4-5	.25	.43	.22	.41	.27	.45
Degree	.05	.22	.04	.20	.06	.24
A level	.14	.34	.13	.34	.14	.35
O level	.05	.22	.06	.24	.04	.20
No qualification	.64	.48	.63	.48	.64	.48
Married on return	.25	.43	.25	.43	.25	.43
North	.08	.27	.09	.29	.07	.25
Midland	.08	.27	.07	.26	.08	.28
North West	.13	.34	.14	.35	.13	.33
Yorkshire	.07	.26	.07	.25	.07	.26
E Anglia	.07	.26	.07	.25	.08	.27
S West	.06	.24	.06	.24	.06	.25
Wales	.05	.22	.06	.24	.05	.21
S East	.18	.38	.16	.37	.18	.39
Old Job Part-Time	.13	.33	.08	.27	.15	.36
Old Job Full-Time	.15	.35	.18	.39	.12	.32
Last Job spell<2 year	.06	.23	.08	.28	.04	.20
Last Job spell 2-5 yrs	.20	.40	.23	.42	.18	.39
Last Job spell 5-10 yrs	.50	.50	.50	.50	.50	.50
Ln predicted hourly wage	1.23	.17	1.18	.17	1.27	.16
Professional partner	.04	.19	.03	.18	.04	.19
Intermediate partner	.18	.39	.20	.40	.17	.38
Skilled non-man. partner	.10	.30	.10	.31	.10	.30
Skilled manual partner	.17	.38	.20	.40	.16	.36
Missing status partner	.32	.47	.27	.44	.36	.48

Table 7.6 Probit Estimates of the Return to Full-Time Work, (Marginal Effects)

Variable	Total		Total		Age<=28		Age>28	
	dP/dx	S. Error	dP/dx	S. Error	dp/dx	S. Error	dP/dx	S. Error
	I		II		III		IV	
Age<28	.050*	.020	.031	.023				
Childcare								
<12 months			-.018	.028	.010	.047	-.030	.034
12-18 mths			-.025	.028	-.033	.046	-.015	.035
18-24 mths			.007	.033	-.062	.056	.038	.041
24-30 mths			-.017	.033	.035	.069	-.026	.037
30-36 mths			-.004	.038	-.128	.049*	.046	.049
Education								
Degree			.057	.078	.036	.134	.066	.103
A level			.014	.041	.096	.075	-.034	.045
O level			.009	.052	.009	.084	.022	.069
No Quals.			-.004	.030	-.028	.050	.011	.037
Married			.068	.024*	.020	.038	.099	.031*
Region								
North			.001	.039	.006	.064	.007	.052
Midlands			.007	.039	-.006	.065	.008	.045
North West			.039	.035	.005	.056	.061	.045
Yorkshire			-.048	.034	-.053	.061	-.047	.039
E. Anglia			-.086	.031*	-.053	.063	-.107	.029*
S. West			-.038	.038	-.040	.066	-.037	.045
Wales			.027	.048	.107	.085	-.033	.052
S. East			-.036	.028	-.049	.048	-.018	.034
No. Children			-.024	.015	-.032	.028	-.017	.018
Youngest <1			-.096	.034*	-.109	.052*	-.108	.035*
Youngest 1-2			-.059	.026*	-.137	.042*	-.020	.035
Youngest 2-3			-.054	.026	-.129	.040*	-.005	.036
Youngest 4-5			-.044	.024	-.065	.044	-.041	.028
Old Job PT			-.065	.026*	-.069	.053	-.061	.028*
Last Job Spell								
<2 year			.042	.053	.035	.078	.004	.067
2-5 yrs			.053	.036	.016	.055	.080	.048
5-10 yrs			.014	.025	.007	.044	.020	.031
Predict. Wage			-.162	.090	-.185	.136	-.148	.128
Partner .								
Professional.			-.057	.046	-.034	.091	-.061	.049
Intermediate			-.014	.031	-.018	.050	-.012	.038
Oth NonMan.			-.020	.035	.031	.067	-.047	.037
Skilled Man.			-.004	.031	-.016	.049	.002	.040
Occup miss			-.006	.028	.009	.047	-.007	.033
N	1628		1628		631		997	
Pseudo R^2	.039		.040		.059		.063	
Sample mean	.180		.180		.210		.160	
Log L	-764.1		-736.8		-305.9		-411.8	
X^2(df)	6.6 (1)		60.3(35)		35.8(34)		53.0(33)	

Note 1. Heteroscedasticity-robust standard errors. 2. Asterisk denote significance at the 5 % level. 3. Specification I II: all mothers. Specification III: mothers who completed a childcare spell before the age of 28 years. Specification IV: mothers who completed a childcare spell after the age of 28 years 4. Dependent variable equals one if return to full-time work. 5. Sample: All females with a completed childcare spell

Table 7.7 Predicted Probabilities of Returning to Full-Time Work

Characteristics	**Total**	**Age<=28**	**Age >28**
A: Sample Mean	.180	.213	.149
B: As default, but less than 12 months in CC, technical qualification, E Anglia with 2 kids (youngest age less than 1) previous job PT, pre-gap spell < 2 yrs, professional partner, predicted hourly earnings, £7.40 .	.008	.036	.001
C: As default, but married between 24-30 months in CC, degree qualification, S West with 1 kid (age 1 - 2) previous job FT, pre-gap spell 2 - 5 yrs, manager partner, predicted hourly earnings, £2.70 .	.254	.242	.540
D: As default, but < 12 months in CC, degree qualification, E Anglia with 3 kids (youngest aged less than 1 year) previous job PT, pre-gap spell less than 2 yrs, professional partner, predicted hourly earnings, £7.40 .	.003	.020	.001
E: As default, but married between 30 - 36 months in CC, degree qualification, S East with 1 kid (age 2-3) previous job FT, pre-gap spell 5–10 years, unskilled non-manual partner, predicted hourly earnings, £4.50 .	.189	.080	.280

Table 7.8 Frequency Distribution of Labour Market States Experienced 1981-91

	Frequency (%)					
Spell no	**Full-time**	**Education**	**Part-time**	**Training**	**Unemploy-ment**	**Child-care**
1	71.5	89.7	66.1	96.5	77.2	75.7
2	21.3	9.2	25.2	3.5	17.1	19.0
3	5.4	1.2	7.0		3.4	4.4
4	1.3		1.1		1.4	0.8
5	0.4		0.5		0.6	0.2
6			0.0		0.1	
7			0.1		0.1	

Sample: All women in NCDS sample

Table 7.9 Average Completed Duration of Spell Types

	Duration (months)	
	mean	standard deviation
Full-time Work	25.7	22.7
Part-time Work	19.1	17.9
Education	17.4	13.1
Training	8.0	5.0
Unemployment	9.5	12.1
Childcare	29.4	24.6
Other	26.9	31.8

Sample: All women in NCDS sample

Table 7.10 Mean Completed Duration, (in Months) of Child Care Spell by Age at Return

Age at Return	All	Full Time	Part Time
	Mean length	Mean length	Mean length
23	5.1	4.3	5.4
24	9.6	10.6	9.5
25	13.2	12.7	13.7
26	19.7	17.2	20.8
27	24.0	21.3	24.9
28	26.4	26.6	27.0
29	33.5	35.6	33.5
30	34.1	32.2	35.0
31	36.0	37.6	35.7
32	40.6	21.2	43.2
33	52.4	34	111.0

Sample: All female returners from childcare

Table 7.11 Kaplan-Meier Estimates for Duration of Child Care

Duration (months)	Fails	Hazard	Survivor	St Errors
1	36	.025	.975	.004
2	42	.029	.947	.006
3	37	.027	.921	.007
4	26	.019	.903	.008
5	29	.022	.884	.008
6	36	.028	.859	.009
12	43	.041	.688	.012
18	30	.035	.571	.013
24	22	.032	.461	.013
30	19	.033	.387	.013
36	22	.046	.311	.012
42	9	.023	.260	.012
48	8	.025	.211	.011
54	5	.019	.177	.010
60	4	.018	.151	.009
66	10	.058	.111	.008
72	5	.041	.081	.007
78	4	.043	.061	.006
84	2	.038	.035	.005
90	2	.067	.019	.004
96	2	.111	.011	.003
102	1	.100	.006	.002
107	1	.250	.002	.001
114	1	1	0	

Note. Sample: All female workers with childcare spell who return to *Employment*

Table 7.12.a. Kaplan-Meier Estimates of Duration of Child Care for Women who Return to Full-Time Work

Duration (months)	Fails	Hazard	Survivor	St Errors
1	10	.007	.993	.002
2	9	.006	.987	.003
3	9	.007	.980	.004
4	10	.007	.973	.004
5	4	.003	.970	.005
6	5	.004	.966	.005
12	5	.005	.934	.007
18	7	.008	.899	.009
24	2	.003	.863	.011
30	3	.005	.836	.012
36	6	.012	.808	.013
42	3	.008	.790	.014
48	0	.0	.770	.015
54	1	.004	.754	.016
60	0	.0	.742	.017
66	0	.0	.702	.020
72	1	.008	.682	.022
78	0	.0	.664	.024
84	0	.0	.619	.030

Note 1. Intermediate months not shown.
2. Sample: All female workers with childcare spell who return to *Full-Time* Employment

Table 7.12.b. Kaplan-Meier Estimates for Duration of Child Care for Women who Return to Part-Time Work

Duration in months	*Fails*	*Hazard*	*Survivor*	*St Error*
1	26	.018	.982	.004
2	33	.023	.960	.005
3	28	.020	.940	.006
4	16	.012	.929	.007
5	25	.019	.911	.008
6	31	.024	.889	.008
12	38	.036	.738	.012
18	23	.027	.637	.013
24	20	.029	.536	.014
30	16	.027	.465	.014
36	16	.034	.388	.014
42	6	.015	.331	.013
48	8	.025	.276	.013
54	4	.015	.237	.012
60	4	.018	.206	.012
66	10	.058	.160	.011
72	4	.033	.120	.010
78	2	.021	.097	.009
84	2	.038	.057	.007
90	2	.067	.034	.006
96	2	.111	.023	.005
102	1	.1	.014	.004
107	1	.25	.005	.003
114	1	1	0	

Note 1. Intermediate months not shown.
2. Sample: All female workers with childcare spell who return to *Part-Time* Employment

Table 7.13.a. Cox Proportional Hazard Model - Duration of Childcare

Variable	**Total I**		**Part-Time II**		**Full-Time III**	
	Coeff	St Error	Coeff	St Error	Coeff	St Error
Age at return 25	.647*	.111	.753	.150	.410*	.144
Age at return 26	.454*	.074	.565*	.106	.200*	.072
Age at return 27	.439*	.068	.520*	.094	.254*	.081
Age at return 28	.389*	.060	.475*	.086	.176*	.056
Age at return 29	.390*	.063	.445*	.083	.259*	.084
Age at return 30	.390*	.069	.427*	.087	.319*	.116
Age at return 31	.407*	.080	.453*	.102	.264*	.114
Age at return 32	.383*	.079	.441*	.104	.228*	.108
Married	1.116	.068	1.040	.070	1.593*	.232
Spouse works	1.625*	.164	1.717*	.192	1.274	.301
North	.903	.127	.949	.147	.745	.252
Midland	.930	.108	.964	.124	.775	.207
Scotland	.989	.161	.958	.173	1.059	.398
North West	.854	.095	.869	.108	.834	.215
Yorks	.871	.113	.960	.134	.484*	.180
E Anglia	.938	.120	.990	.134	.585	.244
S West	.984	.126	1.049	.144	.620	.230
Wales	1.158	.180	1.123	.197	1.252	.431
Previous job PT	2.719*	.176	3.050*	.214	1.497*	.253
Unemp. Rate <5%	.724	.153	.863	.201	.322*	.167
Unemp. Rate 5-8%	.760	.115	.866	.145	.429*	.160
Unemp. Rate 8-10%	.941	.101	1.001	.119	.767	.198
Unemp. Rate 10-12%	.858	:102	.873	.115	.837	.229
Degree	1.081	.192	1.116	.215	.858	.407
A level	.995	.088	1.059	.101	.715	.170
O level	.784	.140	.871	.170	.497	.221
Total No. Children =2	.422*	.030	.419*	.033	.426*	.075
Total No. Children =3	.248*	.029	.216*	.028	.494*	.133
Total No. Children >=4	.276*	.056	.230*	.052	.663	.310
Youngest child age<1	1.429*	.110	1.496*	.126	1.101	.218
Youngest child age 1-2	.623*	.059	.589*	.061	.800	.183
Youngest child age 2-3	.455*	.042	.441*	.045	.501*	.120
Youngest child age 3-4	.301*	.035	.242*	.032	.758	.191
Youngest child age 4-5	.156*	.043	.096*	.033	.953	.473
Partner Professional	1.252	.164	1.279	.181	1.233	.417
Partner Intermediate	1.121	.098	1.154	.109	.919	.217
Partner other non-manual	1.148	.115	1.136	.125	1.201	.303
Partner Skilled manual	1.002	.088	1.002	.096	1.010	.227
Partner Occup miss	1.795*	.189	1.768*	.205	2.004*	.519
Ln predicted hourly wage	1.256	.361	1.406	.444	0.693	.489
N	1406		1406		1406	
No of exits	1406		1182		224	
Log L	-8441.5		-7043.4		-1348.0	
$\chi^2_{(40)}$	746.5		677.8		168.8	

Note. 1. Sample: All female workers with childcare spell. 2. Default categories age<25, single, living in South-East, qualifications less than O level, 1 child aged 5+, non-working spouse, area unemployment>12%, spouse unskilled manual. 3. Asterisk notes significance at 5% level.

Table 7.13.b. Cox Proportional Hazard Model - Duration of Childcare (No Age controls)

Variable	**Total I**		**Part-Time II**		**Full-Time III**	
	Coeff	St Error	Coeff	St Error	Coeff	St Error
Married	1.098	.065	1.024	.067	1.551*	.223
Spouse works	1.582*	.161	1.680*	.190	1.270	.310
North	.859	.104	.875	.117	.815	.239
Midland	.896	.097	.903	.108	.849	.218
Scotland	.928	.137	.871	.143	1.164	.402
North West	.832	.080	.818	.087	.907	.204
Yorks	.823	.098	.883	.112	.516*	.183
E Anglia	.897	.113	.953	.127	.537	.221
S West	.993	.125	1.045	.140	.706	.259
Wales	1.167	.170	1.100	.179	1.437	.468
Previous Job PT	2.742*	.176	3.070*	.214	1.533*	.256
Unemp. Rate <5%	.654*	.078	.733*	.094	.346*	.114
Unemp. Rate 5-8%	.685*	.063	.742*	.074	.449*	.108
Unemp. Rate 8-10%	.882	.072	.914	.081	.773	.155
Unemp. Rate 10-12%	.809	.082	.794*	.089	.920	.214
Degree	1.185	.204	1.124	.231	.853	.396
A level	.996	.087	1.067	.101	.692	.164
O level	.808	.144	.895	.174	.501	.223
Total No. Children =2	.393*	.027	.391*	.030	.391*	.066
Total No. Children =3	.225*	.025	.197*	.025	.411*	.105
Total No. Children >=4	.249*	.050	.204*	.045	.634	.290
Youngest child age<1	1.474*	.113	1.546*	.128	1.129	.220
Youngest child age 1-2	.596*	.056	.565*	.058	.724	.163
Youngest child age 2-3	.436*	.040	.423*	.042	.475*	.112
Youngest child age 3-4	.279*	.032	.228*	.029	.668	.164
Youngest child age 4-5	.144*	.040	.088*	.030	.837	.405
Partner Professional	1.278	.166	1.302	.184	1.232	.415
Partner Intermediate	1.128	.098	1.164	.109	.907	.212
Partner Skilled non-manual	1.136	.114	1.129	.124	1.151	.286
Partner Skilled manual	1.005	.088	1.010	.096	.964	.216
Partner Occup miss	1.774*	.188	1.751*	.204	1.978	.522
Ln predicted hourly wage	0.981	.277	1.079	.333	.664	.468
N	1406		1406		1406	
No of exits	1406		1182		224	
Log L	-8462.6		-7055.7		-1363.3	
$\chi^2_{(32)}$	704.3		653.2		138.1	

Note. 1. Sample: All female workers with childcare spell. 2. Asterisk notes significance at 5% level.

Table 7.14.a. Weibull Model - Duration of Child Care

Variable	**Total I**		**Part-Time II**		**Full-Time III**	
	Coeff	St Error	Coeff	St Error	Coeff	St Error
Age at return 25	.610*	.104	.703*	.140	.404*	.141
Age at return 26	.392*	.063	.476*	.089	.192*	.069
Age at return 27	.377*	.059	.438*	.079	.239*	.076
Age at return 28	.326*	.051	.392*	.070	.161*	.051
Age at return 29	.331*	.053	.374*	.070	.233*	.076
Age at return 30	.347*	.062	.375*	.077	.297*	.108
Age at return 31	.383*	.075	.422*	.094	.263*	.114
Age at return 32	.360*	.074	.408*	.096	.224*	.106
Married	1.099	.066	1.025	.068	1.583*	.229
Spouse works	1.670*	.169	1.760*	.198	1.321	.314
North	.904	.127	.947	.147	.745	.252
Midland	.916	.106	.944	.121	.779	.208
Scotland	1.032	.167	1.009	.182	1.057	.397
North West	.855	.095	.866	.107	.829	.213
Yorks	.899	.117	.994	.139	.492	.182
E Anglia	.986	.124	1.042	.139	.602	.250
S West	.945	.121	1.009	.139	.595	.220
Wales	1.161	.182	1.125	.198	1.250	.431
Previous job PT	2.616*	.168	2.916*	.202	1.491*	.250
Unemp. Rate <5%	.757	.160	.902	.209	.337*	.175
Unemp. Rate 5-8%	.799	.121	.913	.153	.436*	.163
Unemp. Rate 8-10%	.953	.102	1.012	.121	.769	.199
Unemp. Rate 10-12%	.887	.105	.905	.120	.836	.228
Degree	1.209	.214	1.263	.243	.930	.443
A level	1.029	.090	1.102	.104	.715	.170
O level	.757	.135	.836	.163	.504	.224
Total No. Children =2	.428*	.030	.425*	.033	.424*	.074
Total No. Children =3	.272*	.031	.242*	.030	.496*	.132
Total No. Children >=4	.309*	.062	.259*	.058	.689	.320
Youngest child age<1	1.476*	.114	1.556*	.131	1.111	.219
Youngest child age 1-2	.623*	.058	.595*	.061	.787	.179
Youngest child age 2-3	.482*	.044	.478*	.047	.487*	.116
Youngest child age 3-4	.367*	.040	.311*	.037	.781	.190
Youngest child age 4-5	.201*	.055	.129*	.044	1.024	.501
Partner Professional	1.255	.164	1.277	.181	1.242	.420
Partner Intermediate	1.134	.099	1.166	.109	.939	.221
Partner other non-manual	1.155	.115	1.139	.124	1.219	.307
Partner Skilled manual	1.003	.088	1.001	.096	1.013	.228
Partner Occup miss	1.912*	.201	1.880*	.217	2.123*	.549
Ln predicted hourly wage	1.075	.307	1.169	.366	.649	.458
P	1.623*	.035	1.673*	.039	1.412*	.079
N	1406		1406		1406	
No of exits	1406		1182		224	
Log L	-1589.2		-1481.7		-673.6	
$\chi^2_{(40)}$	740.5		661.5		174.9	

Note. 1. Sample: All female workers with childcare spell. 2. Default categories age<25, single, living in South-East, qualifications less than O level, 1 child aged 5+, non-working spouse, area unemployment>12%, spouse unskilled manual. 3. Asterisk notes significance at 5% level.

Table 7.14.b. Weibull Model - Duration of Child Care (No Age controls)

Variable	**Total I**		**Part-Time II**		**Full-Time III**	
	Coeff	St Error	Coeff	St Error	Coeff	St Error
Married	1.079	.064	1.007	.066	1.534*	.219
Spouse works	1.615*	.167	1.714*	.196	1.298	.318
North	.904	.109	.919	.122	.846	.247
Midland	.904	.098	.907	.109	.869	.223
Scotland	1.008	.147	.957	.156	1.199	.414
North West	.863	.083	.851	.091	.918	.206
Yorks	.876	.104	.944	.120	.537	.190
E Anglia	.922	.114	.980	.129	.542	.223
S West	.935	.117	.987	.133	.652	.240
Wales	1.222	.178	1.157	.189	1.469	.479
Previous job PT	2.628*	.167	2.930*	.202	1.511*	.250
Unemp. Rate <5%	.783*	.089	.880	.109	.404*	.128
Unemp. Rate 5-8%	.781*	.071	.852	.083	.491*	.115
Unemp. Rate 8-10%	.934	.076	.969	.086	.806	.161
Unemp. Rate 10-12%	.866	.087	.857	.096	.943	.218
Degree	1.396	.241	1.469	.275	.985	.458
A level	1.041	.091	1.121	.105	.704	.167
O level	.787	.139	.869	.168	.509	.226
Total No. Children =2	.396*	.027	.395*	.030	.387*	.065
Total No. Children =3	.248*	.027	.221*	.027	.416*	.105
Total No. Children >=4	.279*	.055	.232*	.051	.659	.299
Youngest child age<1	1.515*	.115	1.599*	.132	1.136	.221
Youngest child age 1-2	.592*	.055	.567*	.058	.701	.157
Youngest child age 2-3	.462*	.041	.458*	.044	.459*	.107
Youngest child age 3-4	.345*	.037	.293*	.035	.695	.164
Youngest child age 4-5	.183*	.050	.117*	.040	.913	.435
Partner Professional	1.290	.167	1.306	.184	1.253	.422
Partner Intermediate	1.144	.099	1.178	.110	.933	.218
Partner other non-manual	1.139	.113	1.129	.123	1.168	.290
Partner Skilled manual	1.000	.087	1.004	.095	.966	.216
Partner Occup miss	1.882*	.200	1.854*	.216	2.089*	.551
Ln hourly predicted wage	.767	.215	.819	.252	.558	.393
p	1.585*	.034	1.641*	.039	1.348*	.056
N	1406		1406		1406	
No of exits	1406		1182		224	
log L	-1618.7		-1499.91		-690.4	
$\chi^2_{(32)}$	681.4		625.2		141.3	

Note. 1. Sample: All female workers with child care spell. 2. Asterisk notes significance at 5% level.

Table 7.15 Predicted Duration of Returning to Employment

Characteristics	Total	Part-time	Full-time
A: Mean	30.2	30.9	26.8
B: Predicted at means	23.7	26.8	75.6
C: As default, married, degree qualification, North with 1 kid (youngest aged 1 - 2) previous job PT, partner missing occupational status and not in work, unemployment rate 10 – 13 %, age 23, predicted hourly earnings, £7.40 .	10.2	11.5	38.3
D: As default, married, no qualification, Wales with 3 kids (youngest aged less than 1) previous job FT, partner in work in skilled manual job, unemployment rate 8-10 %, age 29, predicted hourly earnings, £3.70 .	50.6	60.4	90.6
E: As default, married, A level qualification, S West with 2 kids (youngest aged 1 - 2) previous job FT, partner unskilled non-manual status but not in work, unemployment rate 10 – 13 %, age 26, predicted hourly earnings, £4.50 .	20.2	22.3	91.5

Table A 7.1.a. Predicted Entry Wage Equation

	1981-82		1983-85		1986-88		1989-91	
	Coef	St Error	Coef	St Error	Coef	St Error	Coef	St Error
Primary	-.028	.118	-.035	.177	-.018	.128	.041	.164
Secondary	-.018	.044	.042	.031	.066*	.032	.053	.050
Constn.	.459	.116	.256*	.160	.038	.092	.040	.145
Distn.	-.079*	.033	-.065*	.028	-.088*	.026	-.072*	.029
Transport	.091	.096	.311*	.141	.162*	.050	.016	.111
Banking	.191*	.051	.054	.060	.099*	.047	.193*	.049
Age17	.019*	.005	.030*	.004	.019*	.004	.014*	.004
Age ^{2}	-.0004*	.0001	-.0007*	.0001	-.0005*	.0001	-.0003*	.0001
North	-.032	.052	-.060	.049	-.072*	.034	-.228*	.053
Mids.	-.124*	.043	-.168*	.040	-.166*	.047	-.138*	.043
Scotland	.077	.044	-.039*	.041	.002	.047	-.221*	.049
North West	-.042	.057	-.088	.048	-.116*	.040	-.101*	.042
Yorkshire	-.118*	.056	-.056*	.040	-.164*	.050	-.116*	.058
E Anglia	-.178*	.065	-.153*	.056	-.098	.051	-.202*	.055
S West	-.145*	.055	-.125*	.049	-.099*	.038	-.199*	.049
Wales	.138	.078	-.079	.057	-.169*	.049	-.159*	.059
Degree	.601*	.045	.454*	.047	.417*	.042	.418*	.049
A level	.026	.041	.114*	.035	.102*	.029	.141*	.033
O level	.056	.047	.072	.046	-.012	.031	.133*	.041
Yr 1 Dum	.096*	.030	-.029	.030	-.043	.029	.010	.032
Yr 2 Dum			-.020	.054	-.015	.025	.049	.034
Constant	.850*	.056	.866*	.054	1.059*	.044	1.043*	.058
N	642		920		1110		845	
Adj. R^2	0.326		0.240		0.225		0.215	

Source: General Household Survey. Note. 1. White adjusted standard errors. 2. Asterisk denotes significant at the 5% level. 3. Dependent variable: Log of the real hourly wage. 4. Sample: All females.

Chapter 8

Conclusion

8.1 Main Findings

The results obtained in this thesis provide a rationale for policy-makers and employers to aid women to regain their pre-interruption earnings profile during a comparatively short period after re-entry to work. It is clear that the loss of skills and knowledge during periods spent outside the labour force have a permanent effect on earnings. Alongside the move to minimise home time periods via flexible working patterns,[1] there is a case to be made for ensuring that the worker's skills and wages rebound to a level which eventually tends to those from before the break. If we assume that an individual's pre-interruption profile is clearly linked to her productivity schedule, it makes little sense for intermittent workers to be locked into wages which are below their marginal revenue product. The investigation of the issues associated with intermittent behaviour is vitally important and the implications of such discontinuous work patterns need to be fully explored in the public arena in order that workers may operate with more complete information sets.

The evidence presented in Chapter 2 formed an overview of the main labour market events in Britain over the last two decades suggesting that women have experienced improvements in workplace fortunes, as measured by employment rates and wages. More women are in work than ever before and their wages have improved in real terms and relative to men. Women also seem to be returning to work after childbirth much sooner than before. However, it is clear that not all women have benefited equally from these changes. It seems that women in part-time work have not enjoyed relative wage gains to the same extent as their full-time counterparts.

Chapter 5 analysed the effect of work interruptions on earnings. We take advantage of a data set that allows us to construct an actual measure of work experience, rather than rely

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[1] Dex and McCulloch (1997) report that, in 1994, one half of women of working age held non-standard jobs.

on the usual proxy of potential work experience. We show that use of potential experience in wage equations may seriously overestimate the returns to work experience. The average wage gain to actual work experience is between 1 to 2 per cent a year. We showed that this return is confined to women with full-time work experience. Additional years of part-time work experience do not appear to add to earnings. This may help explain why the gender earnings gap has not narrowed for women in part-time work. We find that time out of work has an additional negative effect on re-entry wages. Women who take time out experience lower earnings than those who work continuously. The average earnings loss is around 2 per cent a year. The size of this penalty is similar to existing results for the United States. The magnitude of the earnings penalty varies with the type of out of work spell. Those who are unemployed suffer the highest earnings penalty. There is evidence that women who return to work may make up some of their lost earnings, but this is confined to those who are out for reasons other than unemployment or home production. This is consistent with the Mincer and Ofek (1982) view of the restoration period: but only for specific types of time out. The stylised single-peaked lifetime earnings profile is inappropriate in the context of female intermittent workers and the work above provides conclusive evidence for this.

Chapter 6 presented a new decomposition of the gender pay gap which used panel information on employment transitions and wage changes. On entry into the labour market after leaving full-time education, the earnings of men and women are very similar. As earnings growth while in continuous employment shows no significant gender differences, male and female earnings will follow each other closely as long as there are no breaks in paid employment. Differences in wages start to emerge once there are breaks in employment. When returning to the labour market after a break, both men and women do so at lower wages than before, but men return at higher wages than women, with the re-entry gender pay gap rising with age. This, combined with the fact that women are more likely to have breaks in paid employment, is the explanation of why women's pay increasingly falls behind the pay of men over the life-cycle. Women who work part-time are paid less than their full-time counterparts because, first, they are much more likely to be

entrants and, because, second, they have slightly lower wage growth when in paid employment.

As the bulk of the pay gap can be put down to the result of higher numbers of women having breaks in employment and the pay penalty associated with these breaks, this suggests that it is labour market interruptions that are the main cause of women's labour market disadvantage.

Chapter 7 modelled the duration of time spent in childcare more explicitly. As the majority of the interruptions to the labour market careers of women are caused by having children, which is largely a voluntary choice, some might be inclined to interpret the results as saying that a substantial part of the wage gap can be ascribed to the choices of women. We would prefer to interpret this another way. Women are still often forced to choose between career and children, and given this choice, often choose children. However, such a stark choice is not inevitable: maternity leave entitlements can give women some opportunity to have a family and retain their pre-childbirth job. Some 10 per cent of female entrants indicate that they have had a period of maternity leave, but the entry wages seem to be much higher for those who have had leave. So, maternity leave can seem to reduce both the entry pay gap and the share of entrants, which is consistent with a view that it can reduce, or even eliminate, the fall in wages generally experienced when returning to the labour market after childbirth.

Not only do women who take time out to look after children experience significantly lower earnings than those who do not but the longer the length of time out, the larger the earnings penalty. This penalty is magnified if the woman returns to part-time, rather than full-time, work. Chapter 7 identifies the principle features of the duration of time out and the nature of the subsequent re-entry. The average mother by the age of 33 will have spent nearly 2 and a half years out of work in childcare. We have shown that the relative propensity to return to part-time work rises with age of the mother. Women who take child care breaks relatively early in their careers spend less time out of work and are more likely to re-enter to

full-time work. The age and number of children appear to be the most important factors behind this observation. Women are more likely to return to full-time work, the fewer the number of children they have and the older the children are. There appears to be less difference in the length of time out according to education, region, local economic conditions, or predicted income for this group of women. There also seems to be little evidence that women in the age range covered by the NCDS cohort use part-time work as a stepping stone to full-time work.

8.2 Further Research

This work provides a starting point for further debate. Some of the results in this thesis, regarding earnings penalties and the duration of childcare, were for a specific age cohort of women. It would be beneficial to establish whether these results hold across the sample of women as a whole; whether these results change over the period when the gender pay gap has narrowed; whether the pay penalty for resuming part-time work has risen over time; whether the gender pay gap decomposition used in Chapter 6 has changed over time; or how the time spent in child care has altered. Such questions can only be answered with a long run of panel data representative of the population as a whole (as is currently only available for the United States). In time, the BHPS may be able to address some of these questions, but doubts remain as to whether its sample size is sufficiently large to warrant detailed disaggregation.

On more technical matters, because our hourly wage measure is computed by dividing weekly earnings by weekly hours, it is vulnerable to problems caused by measurement error and division bias. Given that very few people seem to move between full-time and part-time status, a high percentage of those who are classed as having moved may be the result of mistakes in coding hours in one of the years. This can then account for the patterns of wage growth seen among those making the transitions. The alternative is that these are manifestations of the part-time/full-time wage gap in Chapter 6. More work on the effects of measurement error on these issues for Britain (in the manner of Brown and Light (1991) for the United States) is needed.

Following Narendranathan and Stewart (1993), we did not attempt to model unobserved heterogeneity in the competing risks framework of Chapter 7. The authors report that existing techniques to deal with this problem produce estimates that are sensitive to the number of competing risks specified and the form of the hazard function. For these reasons, allowance for omitted heterogeneity was left to future work. As with Gianelli (1996), we recognise that any left censored spells present complications when assessing the issue of duration dependence. We therefore restricted our sample to those observations for which we observe entry into the childcare state. In Chapter 7, we used only those observations with completed spells. Due to the nature of the data set, the only censored observations in our sample have to occur at age thirty-three. As we are investigating the impact of age on the process of returning to work, including age variables and allowing for censoring generates collinearity problems. Again this issue would not arise in a data set containing women of different ages.

8.3 Policy Implications

If policy makers are concerned about the negative effects of withdrawal from work that we have observed in this thesis, then it may be that greater provision of childcare facilities may make the return to work easier for those women more marginally attached to the workforce, thereby reducing the length of time out and hence earnings loss. However this alone may be insufficient to encourage women back into full-time, rather than part-time, work. Despite the fact that part-time work is relatively low paid, the majority of women continue to use this type of work in order to combine the worlds of home and work. As this is the outcome of the inter-relationship of the various socio-economic forces at work, perhaps one way forward would be to improve conditions in part-time work. Improving the rights and opportunities of women returning to the labour market after childbirth may be the most practical and effective way to further reduce the gender pay gap.

As Jacobsen (1994) indicates, the expectation that female workers should adhere to a traditional pattern of full-time and continuous work is only appealing if such a pattern were

prevalent in other groups. As the world of work has changed significantly over the past two decades it would seem absurd that such a role for women should be assumed. It may be that combining child care with part-time work should be recognised as an end it itself rather than a transitory state. Attention then needs to be given to ensure that conditions in part-time jobs do not give rise to the penalties witnessed in this thesis.

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